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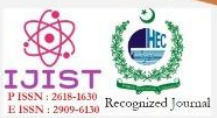

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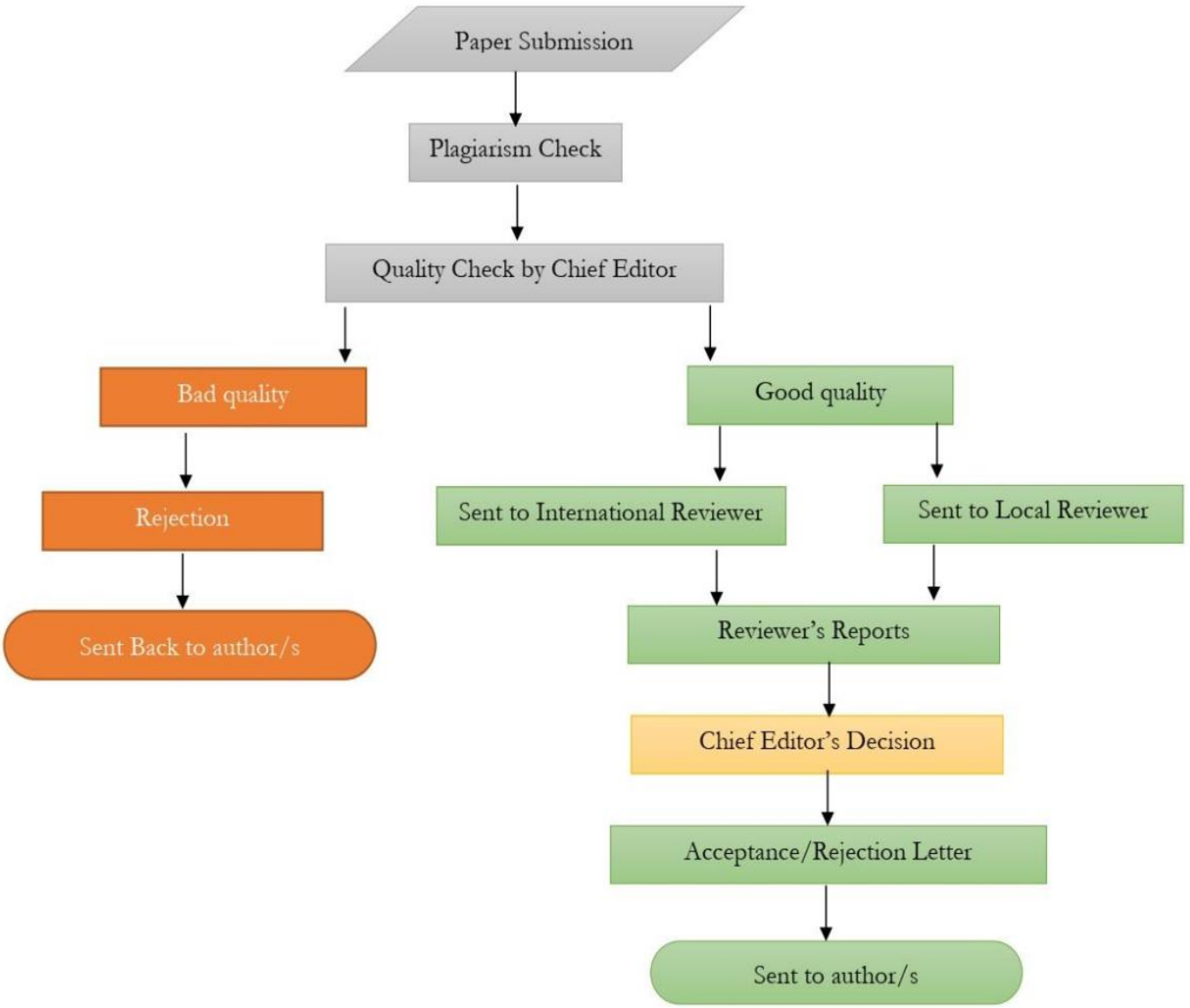

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Isolation of Keratinolytic from Chicken (*Gallus gallus domesticus*) Farms and Assessment of their Efficacy in Feathers Degradation

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ABSTRACT

Keratinolytic microorganisms and their enzymes are associated with poultry feather degradation. In the present study feathers of *Gallus gallus domesticus* (chicken) and surrounding dry soil was collected from a private poultry sheds located in Jahman village near Lahore. Bacteria were isolated by using enrichment techniques and screened for their proteolytic activity on skim agar. Isolated Bacteria were colonially, morphologically and biochemically characterized and named as SNC1, SNC2, SNC3, SNC4, SCH1, SCH2, SCH3 and SCH4. Results showed closed similarity of bacterial isolates with bacillus species. Effect of various media (LB-broth and Nutrient broth), pHs (7 and 8) and temperatures (4, 37, and 50℃) were recorded on bacterial growth and feather degradation. Bacterial cell densities and amount of keratin produced per gram feather weight were high at temperature 50℃ and pH 8.0. The feather degradation by bacterial isolates was confirmed at different time intervals using stereomicroscopes. The protein analysis of *G. gallus domesticus* feathers showed protein contents of 3.125g/100 ml. It was concluded high temperature and alkaline pH favored keratin production by bacterial consortia. Moreover, the bacterial isolates used in the current study have the potential to degrade poultry feather waste and extracted keratin is found to be promising for further exploitation of poultry waste.

Keywords: *Gallus gallus domesticus,* feather biodegradation, keratin waste, *Bacillus* sp.

1. INTRODUCTION

Poultry industry is growing worldwide progressively and generation of waste products from this sector is becoming an environmental issue. These wastes could cause serious soil and water pollution if not processed and discharged properly [1]. Keratinous waste like horns, feather, nails, hoofs, scales, and wools are produced from poultry and meat processing units, slaughterhouses, tanneries and are getting accumulated in the environment [2]. Feathers are considered major waste products that are made up of over 90 % proteins, mainly of beta-keratin which is insoluble and has a very high stability, thus, low degradation rates and can only be degraded by keratinase enzyme [3,4,5]. According to an estimate large quantity of feathers equal to 40×10^9 kg are being produced around the world per year [6]. Nowadays recycling units are installed to make important products such as

feather meal. This feather meal is multipurpose and used as an animal feed, fertilizer and also to produce environment friendly biodiesel [7]. However, only little amount of feathers are processed and are turned into useful products [8]. Furthermore, feathers are being used in cosmetics, textile, plastic and paper industries biopharmaceutical, biomedical and bioenergy companies [9]. Keratin degrading bacteria and their enzymes also have the potential to improve livestock feed resources [10, 11, 12].

The role of keratin in the feather is to make it resistant against proteases such as trypsin, pepsin and papain. The presence of disulfide bonds back off its degradation process in nature [12, 13, 14]. Keratinase is an extracellular enzyme used for the biodegradation and could only be produced by keratinolytic microorganisms in the presence of keratin substrate [15]. Various keratinolytic microorganisms have been already identified in the literature: some species of *Bacillus* (*B. licheniformis* [16], *B. subtilis* [17] *B. cereus* [18], *B. pumilus* [19], actinomycetes and fungi (*Aspergillus* sp. *Penicillin* sp. *and Cladosporium* sp.) [20, 21, 22].

Kumar et al., (2016) have been reported *Bacillus* species to display keratinolytic activity in soil and poultry compost. Keratinolytic activity is related to both, gram negative (*Burkholderia*, *Chryseobacterium* and *Pseudomonas*) and gram positive (*Microbacterium* sp.) genera [23, 24]. However, there is still a gap of knowledge regarding the improvement of the efficiency of keratinolytic bacteria which can be enhanced by environmental conditions. The present study aimed to isolate and characterize keratinolytic bacteria associated with poultry farm soil. Furthermore, they were seen further with varying cultural conditions to see their optimum enzyme production in minimum time period.

2. MATERIALS AND METHODS

Collection of Feathers and Soil Samples

Feathers of *G. gallus domesticus* (chicken) along with dry soil (10 gram soil) were collected in sterile plastic bag in winter season from a private poultry sheds in Jahman village located near Lahore. Its coordinates were 31° 21 0 N and 74° 32 0 E. Samples were collected in the month of December, 2017 and stored at 4°C.

Preparation of Feathers Powder from chicken (*G. gallus domesticus*)

Feathers were washed three to four times with sterile water and autoclaved, for 15 minutes at 121℃. Later on they were further dried in hot air oven for 4 hours at 50℃ and crushed in a grinder machine until a powder form was obtained. The yield of keratin powder obtained from feathers was calculated using the following formula:

Yield of Keratin powder (grams) = Amount of feather powder (gram)/ Amount of feathers used * 100

Isolation and Screening of Bacterial Isolates from chicken (*G. gallus domesticus*) Feather

Bacterial isolation of poultry soil samples was carried out by culture enrichment technique by following the modified method of Kumar et al., (2016). For this purpose, soil (5 gram) was weighed and poured into 250 ml flasks supplemented with 100 ml keratin media (10 g feather powder; 0.5 g NaCl; 0.3 g K_2HPO_4; 0.4 g KH_2PO_4; 0.1 g $MgSO_4.6H_2O$; pH was adjusted to 7.5 using pH meter). The flasks were incubated for one week at 37℃ at non shaking incubator (SKI 4 Innova Bio-Meditech). Later on, 10 ml culture broth from these enriched flasks (containing feather powder) were transferred into a fresh keratin media with freshly added feathers as a carbon source (2.51 grams) and incubated for 4 weeks at 37℃. The sample from enrichment flasks were serially diluted to 10^6 and spreaded on nutrient agar medium. Different colonies were obtained and were further purified by quadrant streaking on the same medium in petri plates. Colony morphology of purified cultures of bacteria were recorded.

Qualitative Screening of Bacterial Isolates for Proteolytic Activity using Skim Milk Assay

Purified colonies were further tested for their proteolytic activity by sub culturing isolates on Skim milk Agar (Hi Media MV763). Five grams agar media was taken with 250 ml water in 500 mL flask and allowed to stand for about 15 minutes. Then the media was placed in a cold water bath and was heated gently with frequent shaking to dissolve the medium completely. Media was sterilized by autoclaving at 15 lbs pressure (121℃) for 15 minutes. Then, it was mixed well and poured into sterile Petri plates. Plates were incubated for a week at 37℃. Bacterial colonies with clearing zones on these plates were used for further characterization. Eight isolates were selected on the basis of zone size and named as SNC1, SNC2, SNC3, SNC4, SHC1, SCH2, SCH3 and SCH4.

Effect of Different Media, pH and Temperatures on Bacterial Growth

To study the effect of varying pHs (7 and 8), temperature (4, 37 and 50℃) and media (L-broth and N broth) on bacterial cell densities, bacteria were cultured in L-broth and N broth adjusted at respective pH using pH meter (one Normal HCl or NaOH) and incubated at respective temperature conditions for 24 hours at shaking incubator. Bacterial growth was determined by taking OD at 600 nm using spectrophotometer (China N6000splus).

Images Analysis using Stereo micrograph and Protein Estimation

The result of feathers degradation was visualized after 4 weeks with stereomicroscope. Protein concentration was determined by the method of Lowry et al., (1951). Briefly, protein is estimated by suspending weighed amount of extracted keratin powder in 30 µl of normal saline (0.9%) (Cappucino and Sherman, 2002) followed by the addition of 120 µl phosphate buffer (0.1M) (Cappucino and Sherman, 2002) in 1:4 ratio. The sample was centrifuged at 14000 rpm at 4℃ for 10 minutes and transferred to ice for 2 minutes. Then, 400 µl of supernatant was taken into separate glass tubes and supplemented with 2 ml of folin's mixture (Cappucino and Sherman, 2002) and allowed to stand at room temperature for 15 minutes. Finally, 0.2 ml of folin's reagent (commercial grade) was added into it and its OD was measured at 750 nm through spectrophotometer (Lowry et al., 1951). The Bovine Serum Albumin (BSA- commercial grade) was used as a standard. The optical density (OD) was read at 750 nm. Protein content is quantified by comparing OD with standard curve of BSA. A standard curve was made by using conc. of BSA ranging 0.1, 0.08, 0.06, 0.05, 0.04 mg/400 µl of saline solution. These different concentration of BSA were prepared in normal saline and subsequently treated in the same way as for keratin powder.

Colonial, Morphological and Biochemical Characterization of the Bacterial Isolates

Bacterial isolates were characterized colonially and morphologically (gram staining, spore staining and capsule staining) following Cappuccino and Sherman, (2002) techniques. Different tests such as Vogues Proskauer (VP), Methyl red, Catalase, Urease, Indole production, Citrate utilization, DNase test, H_2S production and motility tests were performed.

Statistical Analysis

Statistical analysis was carried out between different variables such as temperature and pH using SPSS version 22.0. One way ANOVA was applied on variable temperature treatments. While an independent sample t test was used to analyze pH differences.

3. RESULTS AND DISCUSSION

In the present study soil samples were collected from a poultry site, screened and eight bacterial isolates (SNC1, SNC2, SNC3, SNC4, SCH1, SCH2, SCH3 and SCH4) were selected on the basis of clear zones that were produced on skim milk agar (Figure 1).

Figure 1. *G. gallus domesticus* feather powder

It was noticed in the present study that poultry soil was enriched with microbial diversity with the ability to degrade complex organic compounds. Our findings were in agreement with various studies that showed association of microbes as biodegraders in poultry farms soil [25, 26, 27, 28 29]. Feather degrading bacteria were reported from diverse ecosystems that have a great potential to degrade keratin, however the soil rich in feather is of a great importance due to the excess of keratin [30, 31, 32]. In the study of Lucas et al., (2003), they isolated 33 biodegradable bacteria from dry meadows soil. Bach et al., (2011) also isolated feather-degrading bacteria *(Bacillus, Aeromonas* and *Chryseobacterium* genera) from Brazilian soils. In this study *G. gallus domesticus* feather powder was used for the determination of the keratinolytic activity of keratin degrading bacteria. The feather powder was made of 52.5% protein yield and it was black in color (Figure 2). Protein yield (52.5%) that was identified comparable to protein yield range provided by Lucas et al., (2003) who reported 40-98 %.

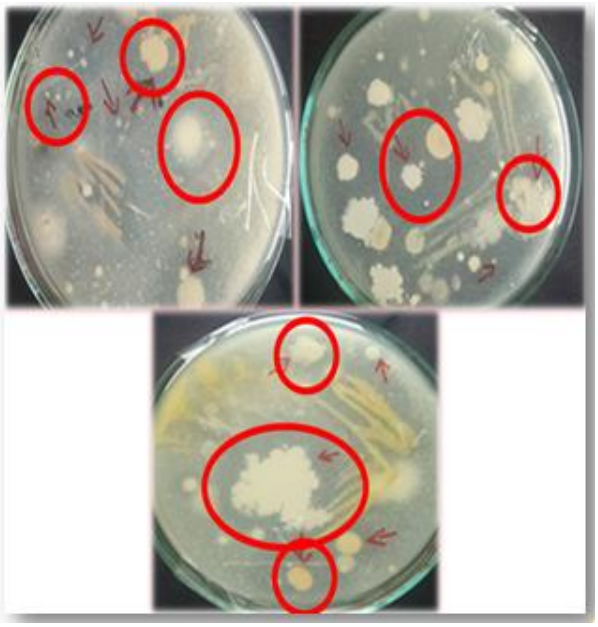

Figure 2. Clear zones on skim milk agar due to proteolytic activity by bacterial isolates (30) obtained from *G. gallus domesticus*

The effect of varying physiological conditions such as type of media (L-broth and N broth), temperature (4, 37 and 50˚C) and pH (7 and 8) influenced on bacterial growth. Bacterial growth in terms of cell densities were high at temperature 50˚C (10^6 CFU/ml) as compared to 4˚C and 37˚C (Figure 3).

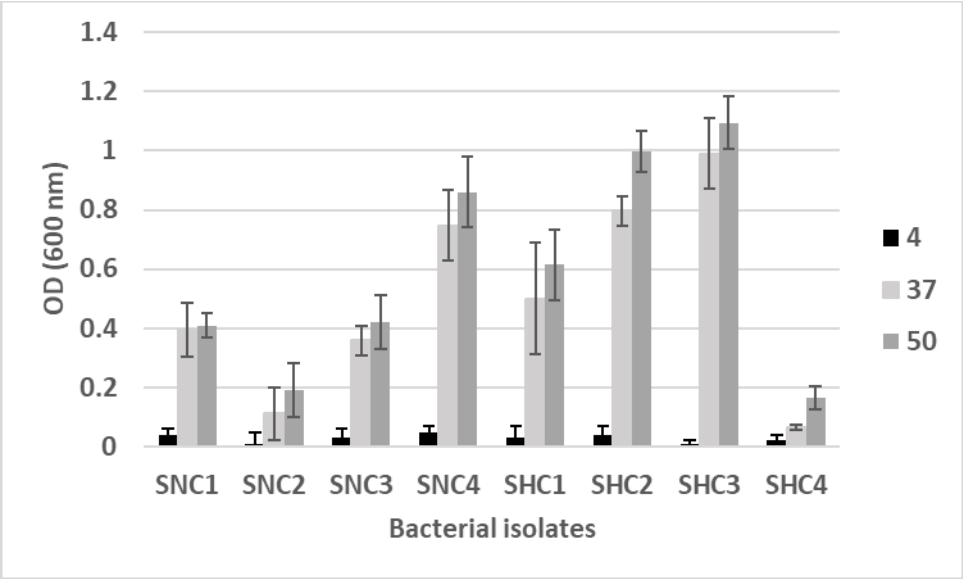

Figure 3. Effect of different temperatures (4, 37 and 50℃) on bacterial growth

The increase in temperature reduced the degradation time of feathers from 4 weeks to almost 3 weeks (Figure 4).

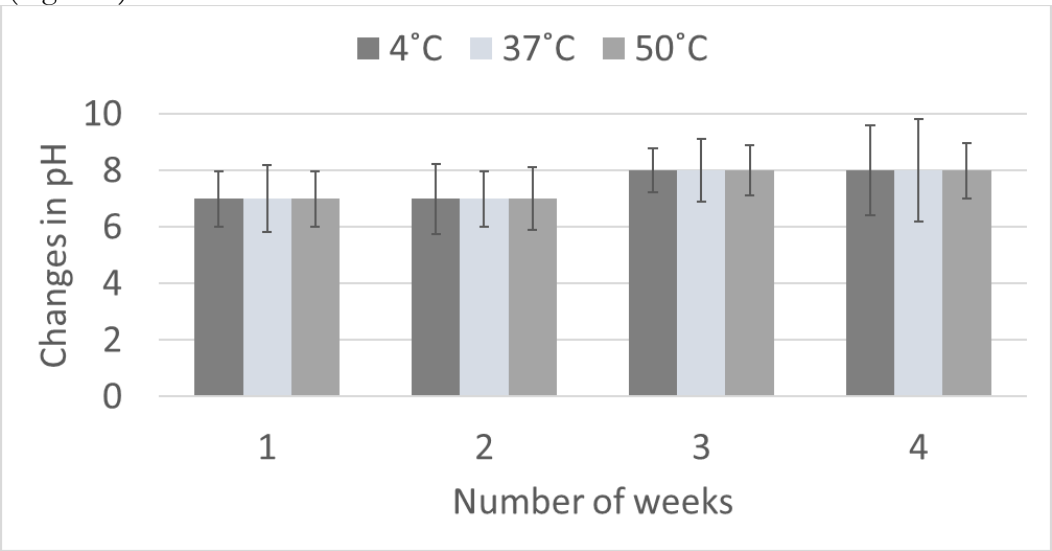

Figure 4. Effect of temperature on degradation of *G. gallus domesticus* feathers (with 10 days interval)

Data was statistically analyzed for one way ANOVA and significant difference (p- value < 0.05) in bacterial growth was noticed at 50℃ temperature as compared to 4 and 37℃. Similarly, bacterial growth was high on pH 8.0 with SCH2 and SCH3 bacterial isolates as compared to pH 7.0, although a maximum bacterial growth was recorded by SNC4 at pH 7.0 (Figure 5).

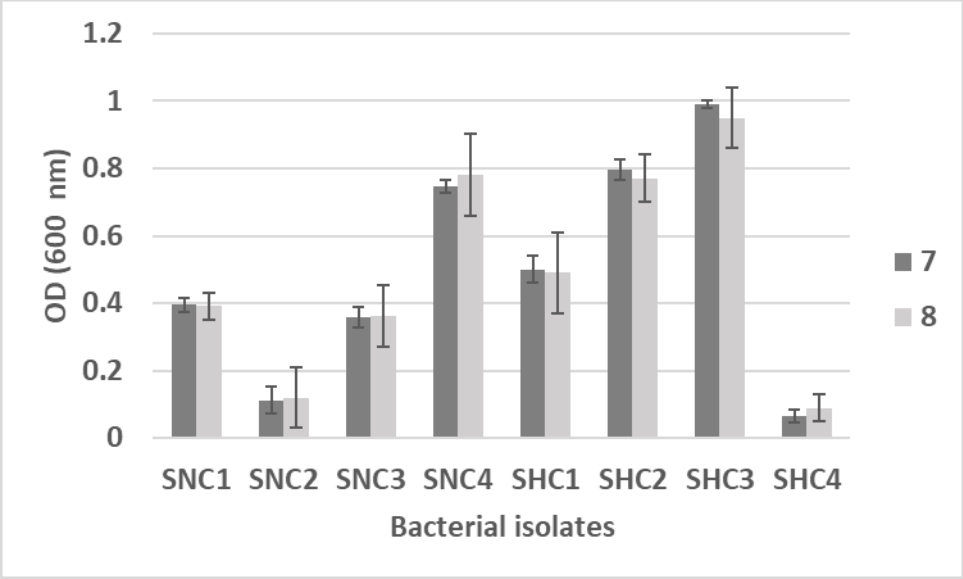

Figure 5. Effect of different pHs (7.0 and 8.0) on bacterial growth

A significant difference in bacterial growth was recorded at pH 8 (p- value < 0.01) using independent sample t test. The increase in pH during cultivation is an important characteristic accompanying keratin hydrolysis and the keratinolytic potential of micro-organisms. Results showed that the increase in temperature and pH causes higher degradation rates (Figure 6).

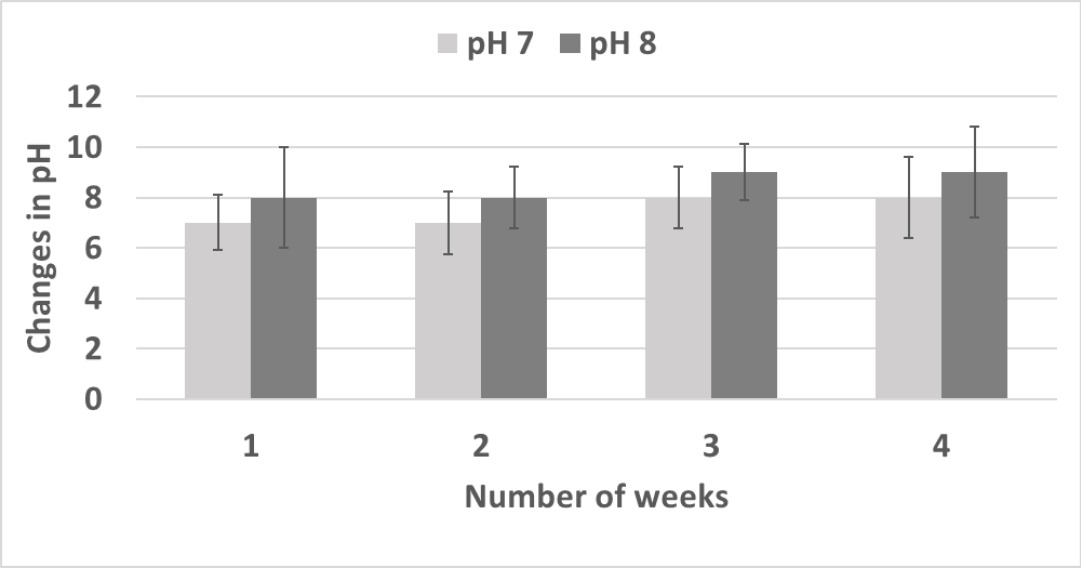

Figure 6. Effect of pH on degradation of *G. gallus domesticus* feathers (with 10 days interval)

Abdel-Fattah et al., (2018) also reported that the biodegradation of feather was greater at a temperature range between 50-60℃ and pH between7-9 with keratinase ALW1 isolated from *Bacillus licheniformis*. Another study with Bacillus species showed best degradation rates between temperatures of 40-50℃ and at 10 pH [33, 34].

Moreover, a comparison was made between samples (flasks with feathers) in the presence and absence of bacterial inoculum and with non-inoculated samples. Bacterial inoculation resulted in a pronounced degradation and the time of degradation was reduced by 10 days as compared to non-inoculated samples. Organisms with a higher keratinolytic activity turned the media into more alkaline, in comparison with other organisms exhibiting lower keratinolytic activity [35, 36, 37]. The protein

concentration of *G. gallus domesticus* feathers was recorded as 3.125g/100 ml and according to the study of Poovendran et al., (2011) the maximum concentration achieved was 7 g/100 ml, which was twice as compared to our results. However, 4.36 g/100 ml protein concentration was reported by Iqtedar et al., (2017) and 4mg/ml was reported by Pandian et al., (2012), whose values were close to our results. The selected isolates were studied for their colonial, morphological and biochemical characteristics and were Gram positive bacteria, spore formers bacteria and rod shaped bacteria. Different tests such as VP (Vogues Proskauer), Catalase, Citrate utilization, and motility turned to be positive. Based on these results of biochemical and morphological characteristics, isolates showed resemblance to Bacillus spp. This was also reported by Mazotto et al., (2011). *Bacillus* strains are able to produce keratinases in the presence of diverse keratinic waste [38, 49] for example from leather industry, barber shop (Kumawat et al., 2017). The majority of reports studying a variety of keratin-degrading actinobacteria and other bacteria, include *Bacillus* sp. [40, 41]. *Bacillus* spp. have been reported to display keratinolytic activity in soil and poultry compost. *Bacillus* spp. have the ability to degrade 50 g/L of chicken feather and produce amino acids and other products with 70 % of conversion rate in 48 hours.

The pattern of feather degradation was observed at different time intervals using stereomicroscopes and shown in figure 7. Degradation of feather was completed at the fourth week and white powdery mass was observed.

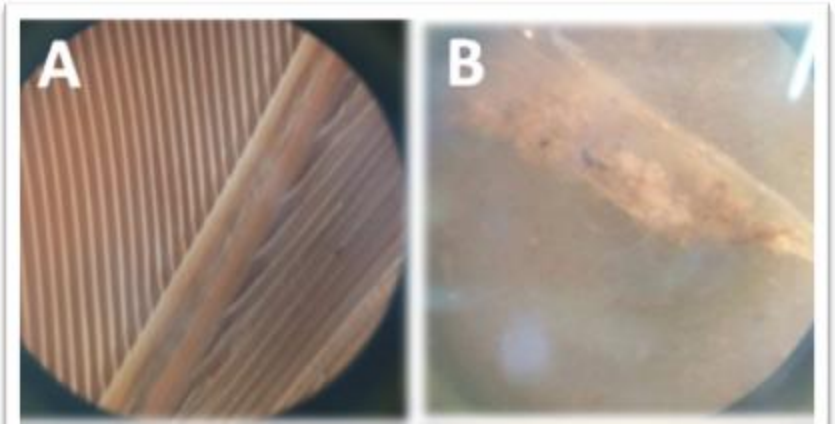

Figure 7. A = *G. gallus domesticus* feather stereo micrograph; B = stereo micrograph of degradation of *G. gallus domesticus* feathers after 4 weeks.

4. CONCLUSION

In the present study bacterial isolates which was mostly *Bacillus* spp. were able to degrade *G. gallus domesticus* feathers from poultry waste using indigenous isolates preferably at high temperature (50℃), and normal pH (8.0 pH). The total protein contents of degraded feather was 3.125g/100 ml. The efficacy of presently used bacterial isolates were found to show the enough potential in degrading poultry waste. Moreover, extracted keratin in present study was promising for further exploitation of industrial use besides poultry waste removal.

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CONFLICT OF INTEREST

Authors declare there is no conflict of interest.

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Riverbank Erosion & Consequent Land Settlement Issues: A Case of River Chenab, District Hafizabad

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Abstract.

When calamity strikes, it causes damage but it also provides opportunities for newer learnings opportunities and better preparedness to combat menace. Pakistan is agrarian economy and comprises fertile plains. According to Pakistan Bureau of Statistics, agriculture contributes to 24 percent of national Gross Domestic Product. Agriculture is dependent on water needs, met through water channels fed by rivers originating mostly from glacial sources existing in northern part of the country. The country hosts five major rivers, namely Indus Jhelum, Chenab, Ravi, and Sutlej. The dendritic river patterns follow gravity flow causing frequent morphological changes and riverbank erosion is the most significant phenomenon which acts as hazard for farming communities in terms of loss of shelter, livelihood, and landholdings. An in-time identification of the issue is the real concern nowadays. Presently, different tools are available for instant interpretation of riverbank erosion like Remote Sensing (RS) and Geographical Information System (GIS), which are not only good for instant identification but also helpful for precise estimation of historical losses. Landsat images for years 2009, 2013, and 2017 have used to make an initial assessment of erosion hotspots. High-resolution satellite imagery from Google Earth is also used for meticulous analysis. The analysis shows that beyond other factors, average riverbank displacement rate due to erosion directly depends on rise in water levels. The study provides systematic bases to estimate the losses precisely. The study is useful for damages assessment of land and livelihood to device relief packages for the affected communities. The study also builds the capacity in resolving land settlement issues consequent to the riverbank erosion phenomenon.

Keywords: Riverbank Erosion; Geographical Information System (GIS); Remote Sensing (RS); Massavi map; Disaster Risk Reduction (DRR); Revenue Land Record

1. INTRODUCTION

Hazard is anything having the potential to harm while the hazards might be natural as well as human-induced. Water needs for the existence of any kind of life on the earth planet can't be ignored right from its beginning. Either we talk about humans, agriculture, livestock, flora, fauna, etc., water is the most important component for their survival. Water on our planet is available by both surface and sub-surface sources. Considering the surficial source, rivers are the biggest water-fed way, fulfilling the basic needs of humans and its related primary necessities like agriculture and livestock. The morphology of any river is defined under natural laws and keeps shifting its channel path with time. This altering behavior of riverbank evolves erosion phenomenon which erodes fertile lands. The decrease in agricultural land and loss of private properties are the most prominent problems that occur due to erosion [1]. Riverbank erosion is a hazard that directly affects the Socio-Economic conditions of the concerned community, leaving landowners deprived in their economic circle and instigating socially marginalized to them as well.

According to one of the reported cases at River Chenab which was published by a daily "Dawn" on March 18, 2015, more than 200 houses & hundreds of acres of land have vanished into the river water [2]. In another similar case reported by a daily "Dawn" on September 22, 2016, the Indus River disturbed residents of 15 villages due to river erosion [3]. Such deprived landowners can be identified as scientifically affected by the river erosion phenomenon and their land-related belongings can also be verified precisely through GIS and RS techniques.

The objective of this study is to identify the morphological behavior of river Chenab with time-series change analysis and to provide scientific evidence for those landownerships that have been affected in history by this phenomenon, leaving them economically disturbed.

2. Material and Methods.

Life without water can't be dreamed on earth and mankind is being benefitted by the rivers for thousands of years. Punjab contains major five rivers, namely Indus, Jhelum, Chenab, Ravi, and Sutlej. Since Chenab River is transboundary and among one of the major rivers flowing in Punjab province. It starts from the Indian "Himachal Pradesh" state and ends at "Uch Sharif" in Pakistan. It is approximately 960 km long. The actual length of any river keeps on changing depending upon the time-to-time change in river meandering [4].

The riverbank change is a geomorphic and climatic agents' behavior that can be identified by studying its historic footprints. These geomorphic agents cause to erode the land on one side while causing deposition to form submerged land on the other side, higher deposition turns the water flow resulting in higher erosion to the mainland [5]. Higher water velocity causes higher riverbank erosion and its rate increases in the absence of vegetation as well [6]. Nowadays, there are different sources to study morphological pattern changes during a certain period at a certain location. RS is the best latest technique to study the river meandering in a more precise manner in a large region [7].

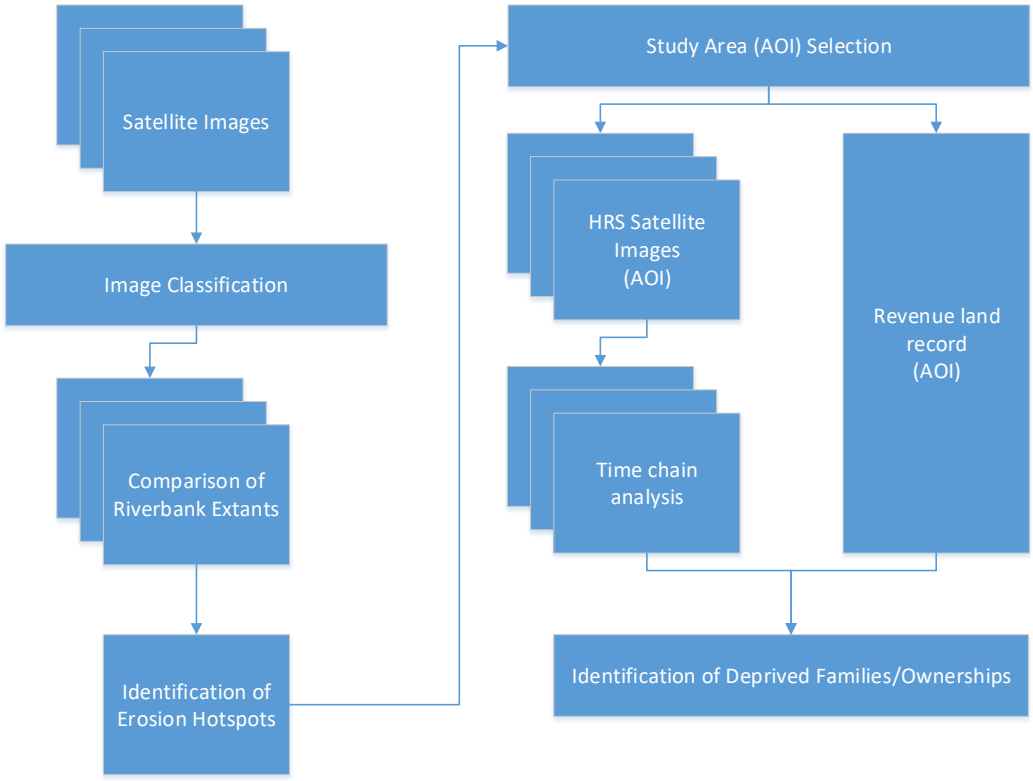

Figure 1. Flow Diagram

Presently, RS is a very powerful tool for river morphological study and remotely sensed data from satellites provides information not only about river channel configuration but also brings many facts about changes in river morphology as well [8]. Satellite RS can play a critical role in determining different forms of damage [9]. These days, many satellite datasets are available at no cost. Landsat satellite imagery is also globally famous for its free sourcing and being used in different ways in multiple sectors [10]. Here, we have also used Landsat satellite images to study the Chenab river's morphological change with time. Landsat satellite has coarse spatial resolution i.e.30m but good enough to work on larger geographic areas. Landsat satellite images from the years 2009, 2013 and 2017 have used for the said purpose. For better precision, satellite images from same satellite and similar dates from repeated intervals should be used [11].

3. Study area

The study falls along the Chenab River within District Hafizabad. District Hafizabad is located at 32.07 N, 73.68 E in Punjab province of Pakistan. Its district boundary from North-East to South-West separates Mandi Bahauddin, Sargodha, and Chiniot districts along the Chenab River. The length of the Chenab River being hosted by the District Hafizabad is almost 67km out of the 101km long shared boundary with its aforementioned neighboring districts.

The Area of Interest (AOI) along the Chenab River inside District Hafizabad is highlighted with the red color rectangle in figure 2 below:

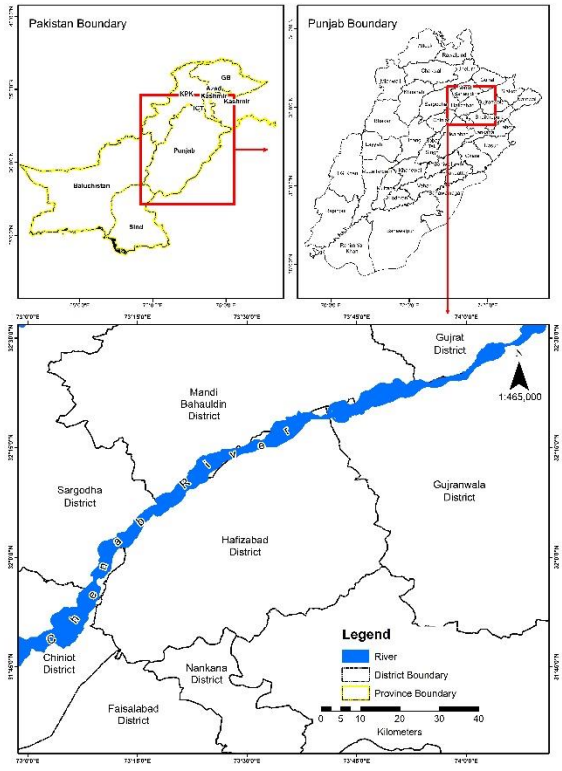

Figure 2. AOI of the Area

Satellite images classification

Object-Based Image (OBI) Classification technique has applied to aforementioned periods' Landsat satellite images to find out the river course change occurred with the time frame.

The separate results of the Chenab river course observed for years 2009, 2013 and 2017 are as shown below in figure 3:

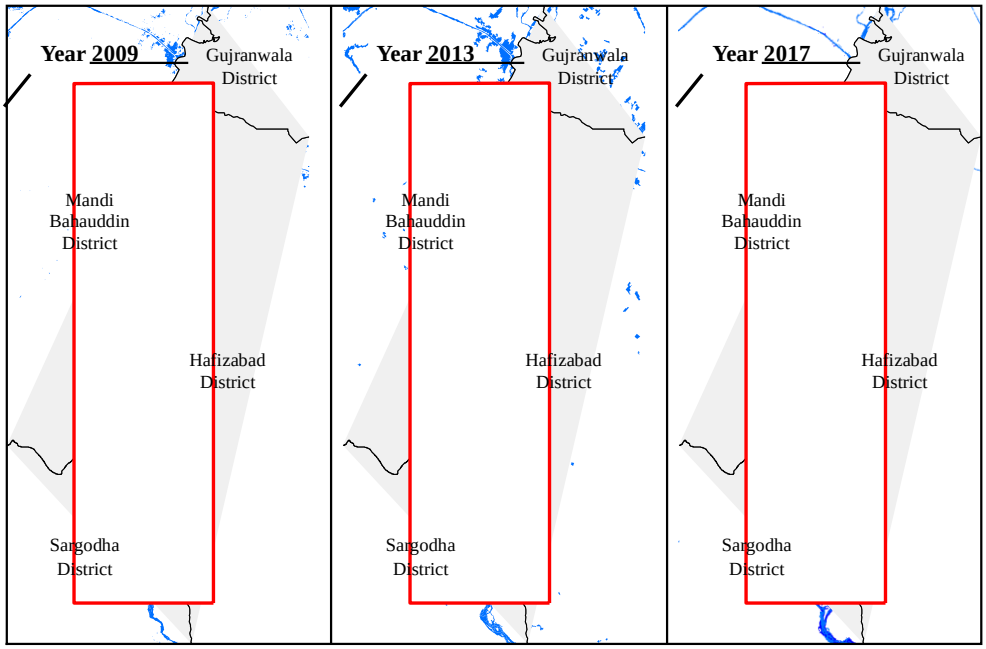

Figure 3. Chenab River channel course by the time

Riverbank extent comparison

The comparative picture of all three years' results is shown in figure 4 below:

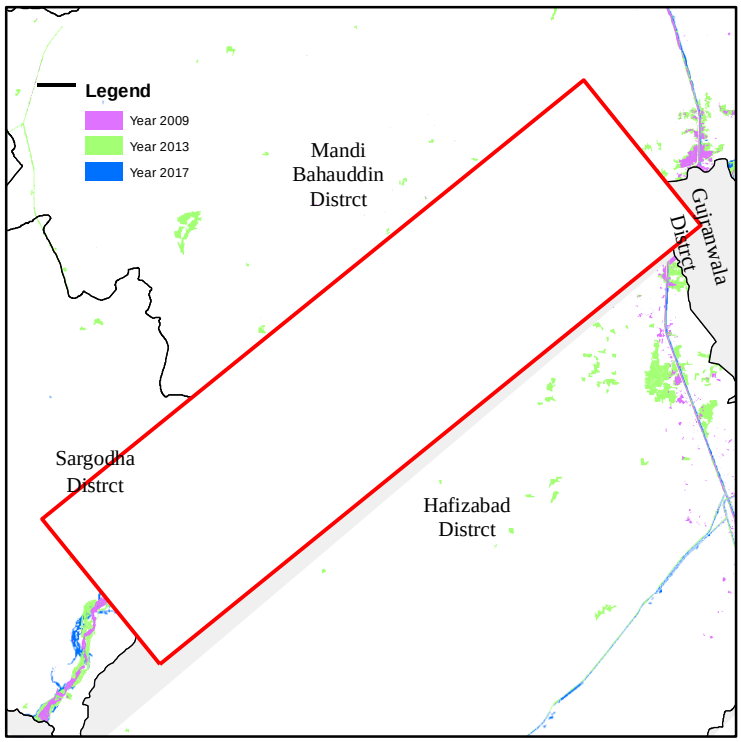

Figure 4. River course for years 2009, 2013 & 2017

Above, figure 4 is important to identify the hotspots in AOI where river course change may be more prominent with rapid change rate and helps to find valuable locations. RS and GIS are efficient tools for change detection [12]. For a layman, change in the river course is just morphological change but in reality, it disturbs the fertile land and leaves concerned families deprived. Riverbank erosion causes destroyed land, livelihood and eventually compelled the people to migrate [13, 14].

The fertile lands destructed by this phenomenon can be identified and such deprived families may be verified scientifically. This study will further focus on the identification of such deprived families through revenue records. For this purpose, there is a need to select one of the hotspots from our AOI as shown in figure 5 below:

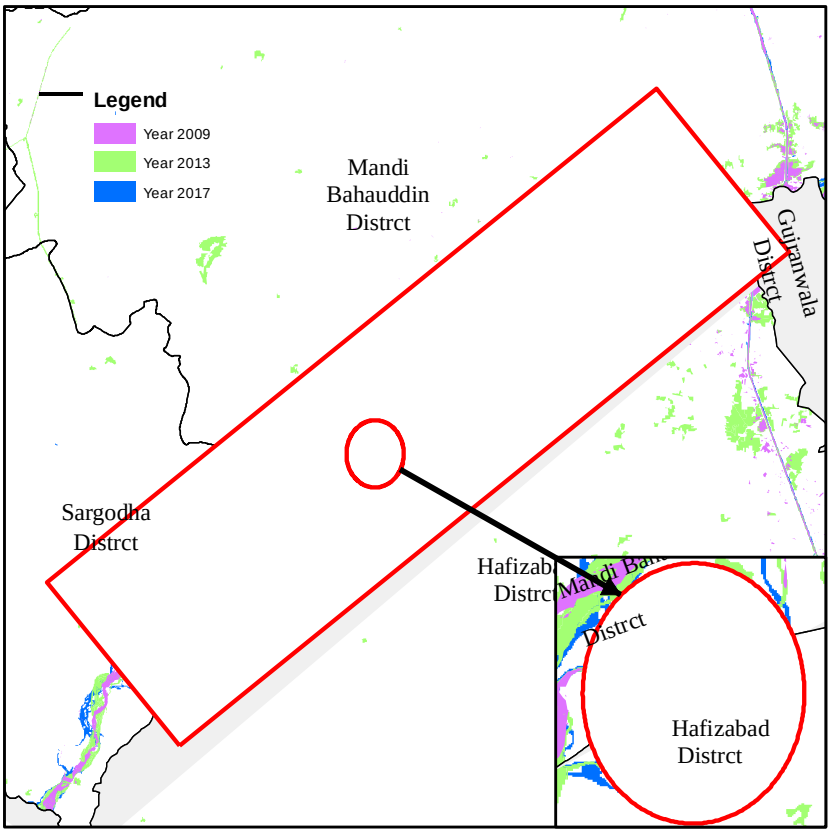

Figure 5. A selected hotspot for identification of deprived families

Erosion hotspots

River erosion is the process of changing river-bed and banks with the time passage. Erosion hotspots/vulnerable points are those locations where riverbank change is visible and it can be observed by comparing riverbank lines for at least two different periods.

In figure 5 above, supports the identification of the river erosion hotspots. Here to proceed, only a single hotspot in District Hafizabad, "Chak Bhatti" along the Chenab River (left bank) has been selected for detailed working. This position is available at 73.39 E, 32.16 N.

Revenue land record

For precise identification of deprived families due to river erosion phenomena, there is a need to register the revenue land record document (Massavi map, contains individuals' land ownership information). It is possible to make geo-referencing of Massavi map, applying the GIS techniques [15,16]. For the said purpose, the Massavi map of "Chak Bhatti" (shown in figure 6 below) can be geo-tagged and the processed Massavi map results are shown in figure 7 below:

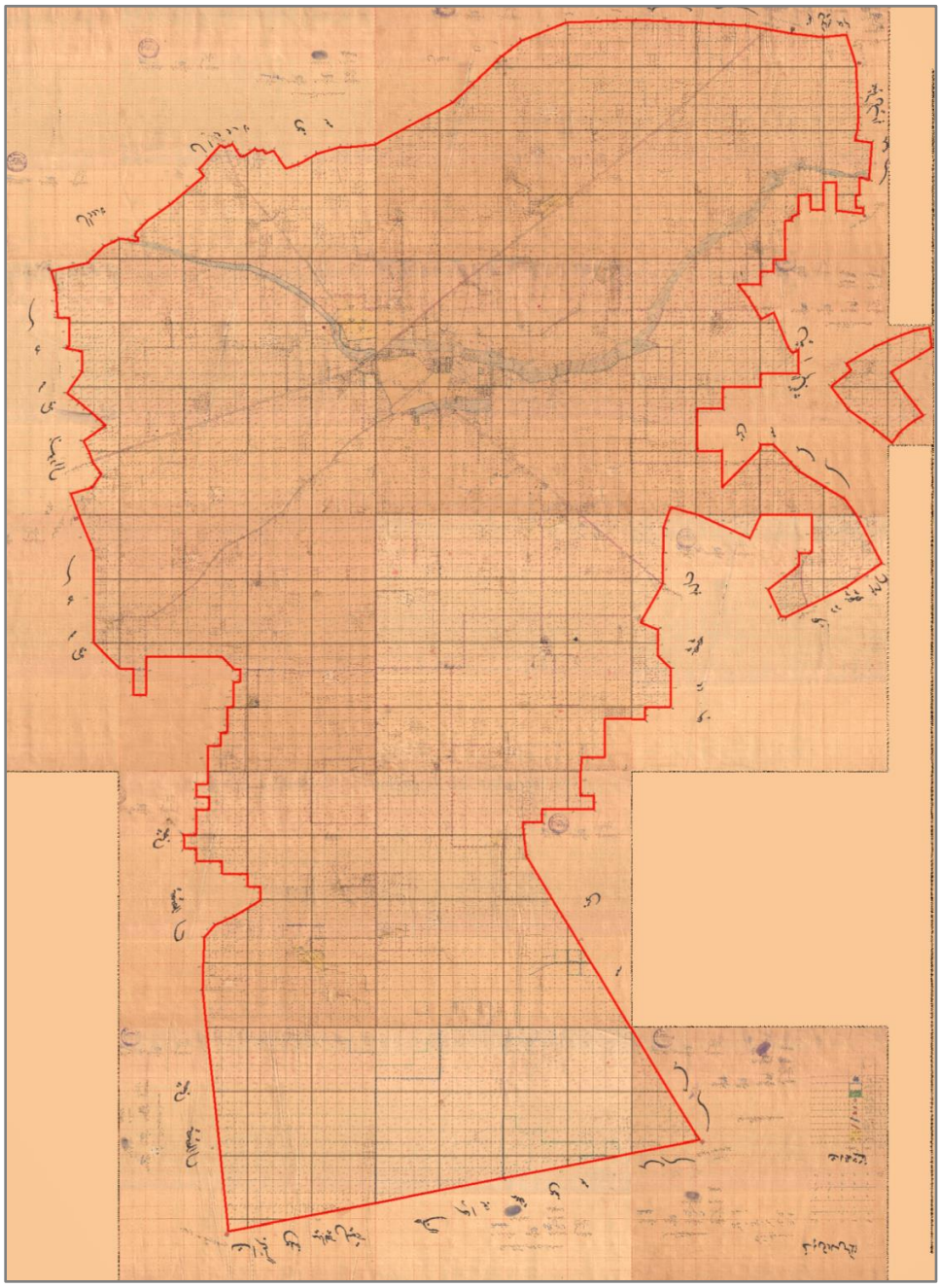

Figure 1. *Massavi* map (revenue record) of Chak Bhatti, District Hafizabad

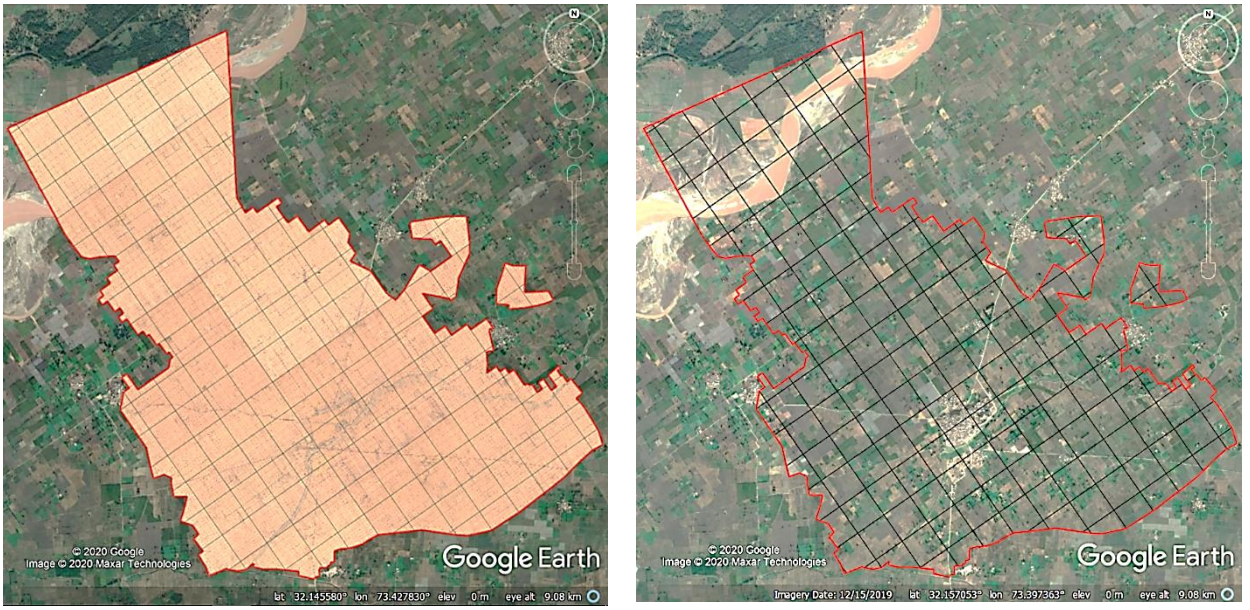

Figure 7 and figure 8. are showing comparative pictures and ground linear features can be matched easily for evaluation as well.

Analysis

More than 75% of the world's Ice-free land showed evidence of human alteration as a result of shelter and land-use activities [17]. Riverbank erosion causes may be natural and/or human. Riverbank erosion has negative impacts on human life, conversely human activity has a negative impact on riverbank erosion [18]. The erosion phenomenon shapes our riverbanks which depends on river water level and soil properties [19]. To understand the actual changing ground situation due to riverbank erosion with the time can be determined through high-resolution satellite imagery. Google earth's "Show Historical Images" tool has been used for highlighting the situation and time to time change found in riverbank displacement is as shown below:

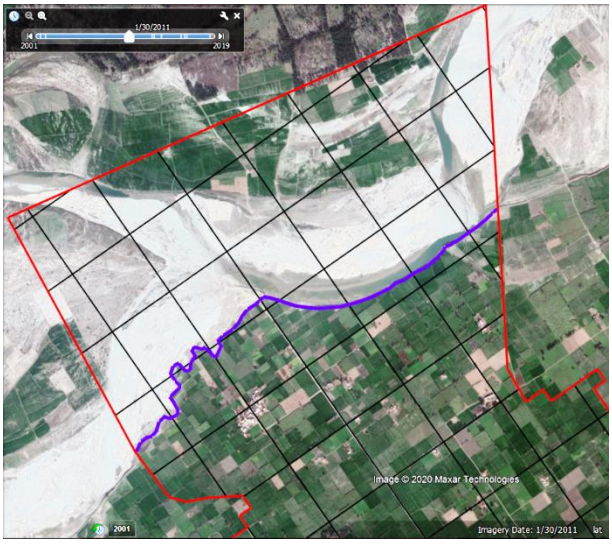

Figure 9. Riverbank line as of Jan 30, 2011

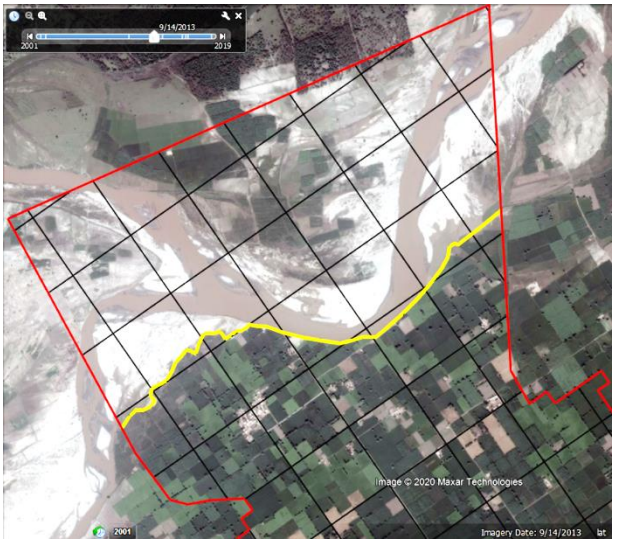

Figure 10. Riverbank line as of Sep 14, 2013

Figure 11. Riverbank line as of Oct 17, 2016

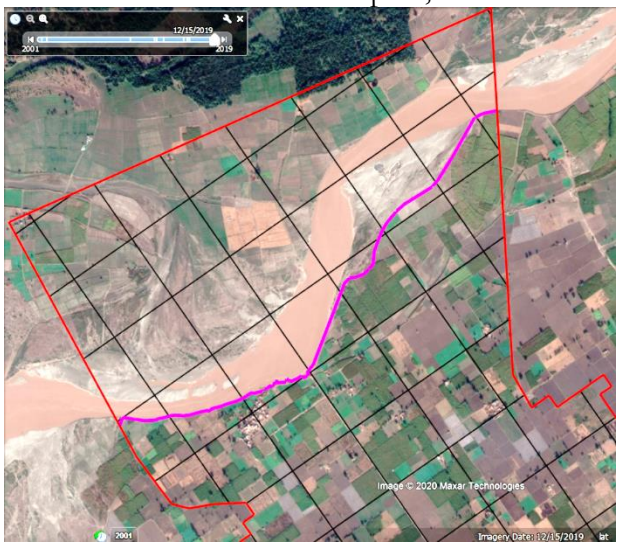

Figure 12. Riverbank line as of Dec 15, 2019

4. Results & discussion

A complete comparison of all time riverbank shifts has (separately shown above in figure 9, 10, 11 & 12) displayed in figure 13 below:

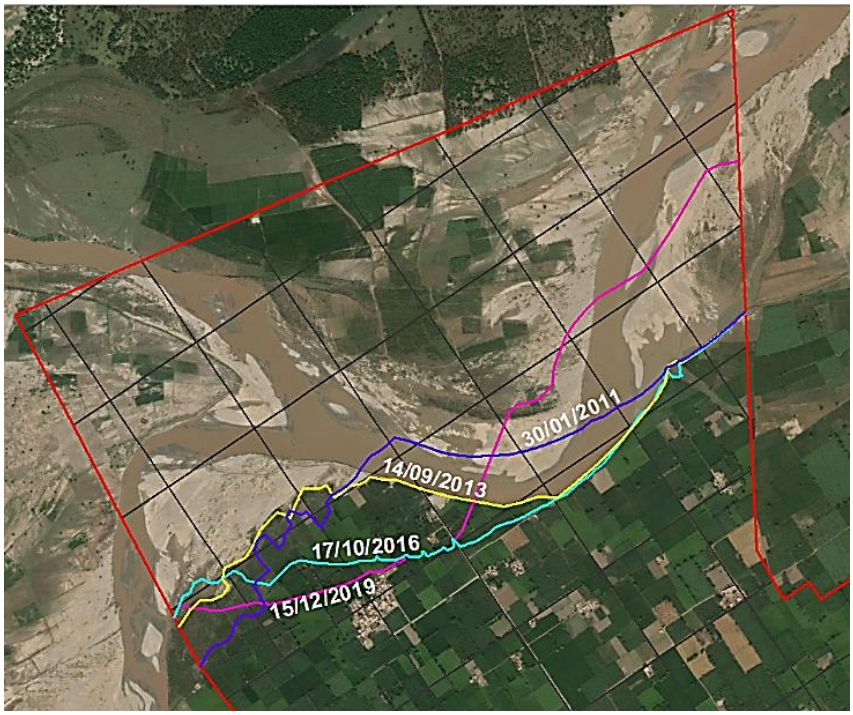

Figure 13. All time riverbank shifts' comparison

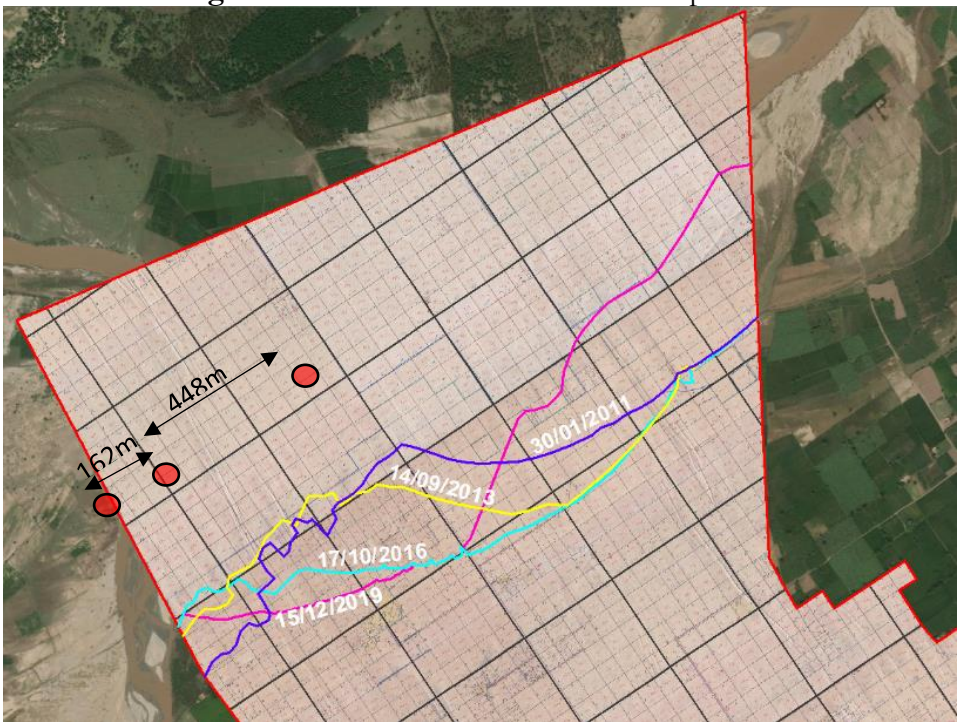

Figure 14. All-time riverbank shifts along with Massavi map (revenue record-keeping document)

Figure 13 shows that how the riverbank is eroding land with time, it also shows that riverbank displacement from 2013-16 is more than any other span which reflects the effect of 2014's super flood faced during this period. The joining points of riverbank displacement lines between 2013-16 and 2016-19 show 448m and 162m shift in South-West along with the river flow, respectively. This shows that the average riverbank displacement due to erosion phenomenon at this location was 12.1m/month and 4.4m/month during 2013-16 and 2016-19, respectively. The victims face economic, social and health insecurities and make families' life more vulnerable [20], however, regular monitoring of riverbank erosion values and soil degradation can help to foresee the situation [21]. Families settled along the riverbank used to face many problems in their daily life due to issues like frequent floods and riverbank erosion [22]. On the other hand, bad governance also acts as a catalyst for the miseries of the affected community [23]. Therefore, it is needed to monitor the erosion phenomenon on regular basis to save the vulnerable communities otherwise it may turn to serious consequences as well [24]. Many remedial measures may be taken including concretization, plantation, desilting, use of nut-fibers and synthetic erosion-resistant mats [25]. Soil can be divided into different types based on erosion rate and accordingly plantation plans can be suggested, like land with heavy grade erosion can be planted by sugarcane and with low grade erosion can be corn or rice [26].

Table 1. Land losses in different years

Image Date	Total Area Eroded	
	Sq Meter	Acre
1/30/2011	2,305,246.5	569.6
9/14/2013	2,376,378.4	587.2
10/17/2016	2,542,732.1	628.3
12/15/2019	2,203,017.5	544.4

The table 1 is showing the information regarding capture dates of different satellite images used in this study and the submerged area of Chak Bhatti on the given date. The results shown in this table describe that on 30th January 2011, the eroded area of Chak Bhatti due to riverbank erosion was 569.6 acres while on 14th September 2013 the submerged/eroded area was increased to 17.6 acres, leaving total of 587.2 acres of area eroded. Similarly, as on 17th October 2016 the submerged/eroded area of Chak Bhatti kept on damaging land in Chak Bhatti with increase of 41.1 acres during the period of almost 3 years and hence the total eroded area increased to 628.3 acres and the further analysis shows that on 15th December 2019, the riverbank shifted its mender to leave some submerged area of Chak Bhatti to dry part which resulted as decrease of 83.9 acres, keeping total of 544.4 acres submerged.

5. Conclusion.

The implementation of modern techniques (like RS and GIS) is not only greatly helps to study the riverbank erosion phenomenon but also be very precise to accurately identify

the affected landowners. Figure 14 is self-explanatory to identify such ownerships as geo-referenced revenue land record has shown with the time-to-time riverbank displacement extents which geo-tags all the affected ownerships very precisely. This study at work has multiple benefits in the larger disaster management realm, but more specifically it is highly useful in:

- Precision land loss and reclamation estimations due to riverbank erosion phenomenon
- Devising prompt and efficient relief packages for the riverbank erosion affectees by relief agencies
- Enhanced disaster preparedness levels at the community and government levels.
- Adaptation of the riverbank erosion phenomenon, sometimes these are beyond our control and means.

It has also been observed that the victims of the riverbank erosion phenomenon are not provided any compensation against their eroded lands which of course pushes the victimized families to financial stress. Because of the above findings, the study also suggests a suitable scientific-based stipend for the victimized families, since water charges (Aabiyana) are being collected by the government from other harvesters and this availability of water for the crops is being made possible through such affected owner's private lands, as well.

Conflict of interest. Authors have no conflict of interest for publishing this manuscript in IJIST.

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Analysis of Pesticides Residues in Breast Milk of primiparous and multiparous women in Gilgit

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Abstract.

Milk contains all the essential nutrients like fats, proteins, and minerals. The utilization of contaminated food can induce a proportion of pesticides in the body. The main purpose of the study was to determine the pesticide residue and current status of Breast milk in primiparous and multiparous mothers. In a current study, a total of 50 samples were collected from different areas of Gilgit and Astore. The pesticides cypermethrin, deltamethrin, and chlorpyrifos were analyzed using Gas Chromatography (GC). The present study shows analysis of the variations among the sample. The presence of cypermethrin in 10 samples ranged between 0.00 – 0.012 mg/kg, while the detection of Deltamethrin in 07 with variation from 0.000.12mg/kg. Whereas chlorpyrifos was found in 05 samples within the ranges of 0.00-0.0062 mg/kg respectively. Residue level was quite higher in urban areas than rural areas. The multiparous women had prominent residues level than primiparas and the concentration of Deltamethrin was higher than other pesticides. All the pesticides residues levels in the breast milk of primiparous and multiparous mothers were within the limits of WHO. Yet the women of these areas are not vulnerable but prolong exposure may pose a serious threat to neonatal and maternal health and other relevant reproductive issues.To manage the risk of milk contamination in the future, the demand for public awareness campaigns and the adoption of alternative clean approaches to control pests and other disease-spreading vectors in the best interests of public health seems reasonable.

Keywords: Gas Chromatography, Milk,Multiparous , Pesticides, Primiparous.

1. INTRODUCTION

Pesticides are used to protect crops, control damage, and maximize crop production. Different pesticide groups were in use including Organochlorine, Organophosphorus

pesticides, pyrethroids, and carbamate, pesticides whichcontains toxic compounds that are banned [1].Breast milk is the only source of diet for growing children it contains all the essential nutrients required for the development of newborns such as proteins, fats, and carbohydrates. Unluckily nowadays breast milk is not pure it is contaminated with toxic substances [2,3].

pesticides are extensively used throughout the world for enhancing food production, controlling pests,and insects, and destroying the vectors of human and animal diseases like malaria, dengue, encephalitis [4]. Consumption of toxic chemicals through the field, diet, or through inhalation and dermal contact, may cause instability in daily life. Organophosphorus pesticides are lipophilic and are more persistent in breast milk [5, 6].In Pakistan farmers use different types of pesticides for the betterment of crops, it includes 39 types of herbicides, 108 insecticides, and 30 fungicides. Farmer's usually used Organochlorine, Organophosphorus, and alternate of urea. Residues are extensively found in different areas of Pakistan due to their unrelenting nature. When mothers consume contaminated food, level of residue rises in the body [7, 8, 9]. According to an economic survey 2012-13 of Pakistan locally 30,000 tons of pesticides were manufactured and 12665 tons were imported. In Pakistan mostly pesticides are used in fields which isan alarming situation for the presence of residues in food [10].

Human milk is thought to be the natural superior food for infants to meet their nutritional needs as they grow. Human milk, on the other hand, is an ideal matrix for the accumulation of pollutants. Chlorinated pesticides were common chemicals in the previous century's environment. They were widely used to control agricultural pests all over the world, and they are still used in some countries to control the malaria disease insect vector. When newborns and infants are exposed to these pollutants through feeding, they may suffer from lower birth weight [11], neuro-developmental delay [12].

Pregnant women are primarily exposed to these compounds through their diet [13], particularly through fish, meat, and milk [14, 15]. Despite a decades-long global ban on the use of OCPs, residues have been discovered in breast milk all over the world [16, 17, 18, 19].

Human breast milk is an ideal marker for OCPs because it provides information on the toxic effects of these substances on mothers and newborns. Pesticide accumulation in breast milk can be influenced by a variety of factors, including diet, place of residence, smoking, maternal age and weight, and previous lactation duration; however, the literature provides conflicting information [20].

2. Material and Methods.

Study Area. Samples have been collected from five areas of District Gilgit (Danyore, Chilmis, Nomal, Gilgit City, and Oshikhandas) and five areas District Astore (Eidgah, Nowgam, Fina, Patipora, and Pakora).

Sample collections. 50 Samples were collected from volunteer mothers primiparas and multiparas between the ages of 20-40 before they are enrolled in the study all women signed authorization. Around 40ml milk was collected in 100ml sterilized glass bottles with identification codes and placed in an icebox during the collection period and stored in a freezer at -20 C until laboratory analysis.

Samples have been collected during a period of two months from November to October 2019 from mothers who were either native to or lived there for thelast five years. A questionnaire has

been designed to access the socio-demographic data, food habits during and after pregnancy, age, and residence.The selective criteria in the currentstudy were followed in previous similar studies. A self-administered questionnaire was also employed to acquire information about the subject's age, parity, body mass index, eating habits. Questions regarding demographic characteristics and feeding habits were modified by Environmental Protection Agency EPA (21).

Laboratory Analysis.

1ml of milk sample and 15ml of acetonitrile containing 0.01% acetic acid were mixed in a polytetrafluoroethylene (PTFE) centrifuge tube. Shaken the samples vigorously for 02 minutes and sonicate samples for 10 minutes. 6g of anhydrous MgSO4, 1g of NaCl, and 1g of sodium acetate trihydric were added to the sample. Again shaken the sample for 02 minutes and centrifuged for 05 minutes at 400rpm. The supernatant of 8ml was transferred into another PTFE tube and added 1g of MgSO4 and Florisil. Again centrifuged the samples and transferred the upper layer into a round bottom flask and left to evaporate until complete dehydration using a Rotavapor. Then reconstituted in 1ml of n-hexane containing 10-15% acetone and finally analyzed the sample through GC.

Statistical Analysis:

Obtained data were précised as mean. ANOVA and LSD were applied to check to mean the difference among samples by using SPSS 21 and Statitix 8.1 Capital letter represents LSD and Significance difference among means in column-wise.

RESULTS AND DISCUSSIONS.

Table 1. Mean value of pesticides residue area wise in mg/kg

Locations		Cypermethrin	Deltamethrin	Chlorpyrifos
Astore	**Pakora**	0.012^{A}	ND^{A}	0.005^{A}
	Nowgam	0.001^{B}	0.01^{B}	ND^{B}
	Patipora	ND^{C}	ND^{AC}	ND^{BC}
	Fina	ND^{CD}	ND^{ACD}	0.002^{D}
	Eidgah	0.011^{AE}	0.002^{E}	ND^{BCE}
	Oshikhandas	ND^{CDF}	ND^{ACDF}	ND^{BCEF}
	Chilmis Das	ND^{CDFG}	ND^{ACDFG}	ND^{BCEFG}
Gilgit	**Nomal**	0.0012^{H}	0.015^{H}	ND^{BCEFGH}
	Danyore	0.00574^{I}	0.00528^{I}	0.0062^{I}
	Gilgit City	0.0005^{J}	0.12^{J}	ND^{BCEFGJ}

Note: ND: Not Detected

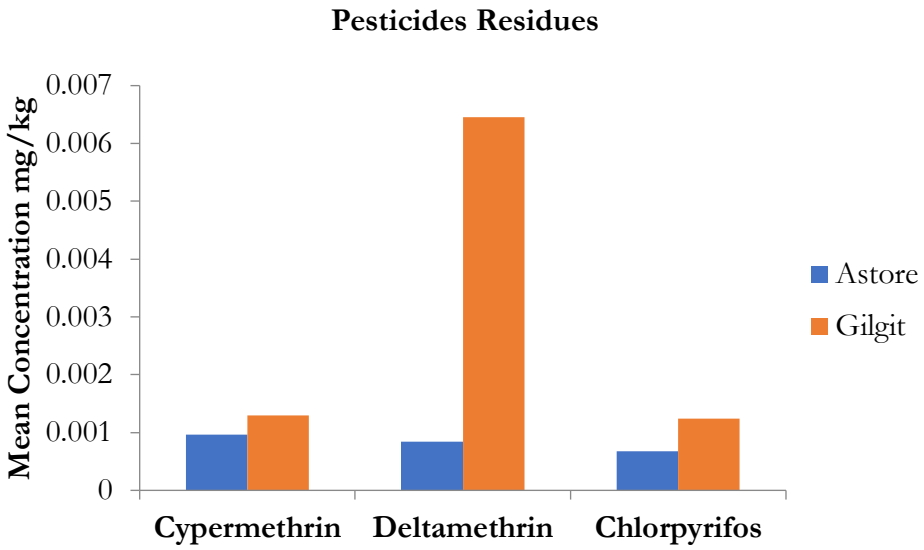

Figure1. Mean concentration of pesticide residues in District Astore and Gilgit

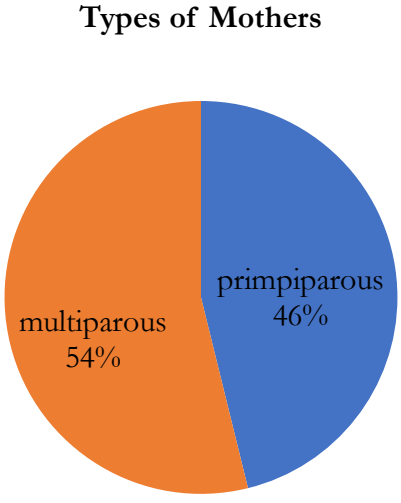

Figure 2.percentage of primiparous and multiparous mothers

In a current study, three pesticides were under observation named Cypermethrin, Deltamethrin and Chlorpyrifos from breast milk, 54% of mothers were multiparous and 46% were primiparous among selected mothers for sampling shown in figure 2. Out of 50 samples, 13were detected with pesticide residues. The residues of Cypermethrin were found in 10 samples maximum value was found in Danyore0.014mg/kg and the minimum value was obtained in Nowgam 0.001mg/kg.Deltamethrin in 09 samples maximum value of 0.12mg/kg was found in Gilgit and lowest 0.001mg/kg in Eidgah. Chlorpyrifos was found in 05 samples highest value in Danyore 0.019mg/kg and lowest in Fina 0.002mg/kg. The result shows that all the samples have residues of pesticide among them Cypermethrin was the major contaminant in milk samples mean values are shown in table 1 and figure 1. Residue level in all samples was lower than the MRLs set by FAO/WHO.

In the current study, Cypermethrin residues were found in 7 samples of District Gilgit highest residue level was obtained in the sample of Danyore and the value was 0.014mg/kg and the lowest was found in Nomal and Gilgit with the residual level of 0.0012 mg/kg and 3 samples from Astore have the residues of cypermethrin maximum value was present in the sample of Pakora 0.012mg/kg minimum value in Nowgam 0.001mg/kg. To analyze the presence of Pyrethroids in human milk a study was conducted in Columbia. The residues of Cypermethrin, permethrin, and fenvalerate were present in the samples. Pyrethroids were useful to control Dengue and the level reach28ngg-1/W. Evaluation of daily intake in nursing infants was calculated and compared to an adequate WHO level [22]. A similar study was conducted in urban and agricultural areas in Mexico on lactating women. The concentration of pp-DDT and cypermethrin in breast milk was higher in those women who are living in urban areas than in agricultural areas ($p < 0.05$and $p = 0,001$). Since pesticide levels do not exceed the ADI according to EPA and FAO/WHO [23]. The study investigates the residues of chlorpyrifos and other pesticides in cow's milk from Punjab India show CPS, DDT, and HCH as the major contaminants. Also the presence of cypermethrin, cyhalothrin, fenvalerate, deltamethrin, Malathion, profenofs, andehion was reported. 12 samples exceed the maximum residue limits (MRLs) for lindane, 18 for DDT, 1 sample for chlorpyrifos, profenophos and cypermethrin [24].

The current study shows that the residue level of Deltamethrin was presented in 09 samples among these 6 samples are from different areas of District Gilgit and the maximum value 0.12mg/kg was found in Gilgit-city and the minimum value detected in Danyore was 0.0011mg/kg and 3 samples are from District Astore the maximal value is obtained in Nowgam and Eidgah 0.01mg/kg and minimal value in Eidgah 0.01mg/kg. A similar study was conducted for the determination of nine pesticides. The residues of Deltamethrin, trifluralin, cypermethrin, endosulfan, HGH, p'p'DDE and p'p-DDT were found in breast milk. Still, mothers were subjected to feeding infants because breast milk is considered as nutritive food during infancy [25]. A study was conducted in Punjab to monitor the residue level of various pesticides (DDT, DDE, cypermethrin, deltamethrin, permethrin, aldrin, and bifenthrin) 70% of samples were contaminated. DDE, DDT and endosulfan were present in minor proportions. Bifenthin residues are higher among Pyrethroids with a mean concentration of 1.68µg/ml, cypermethrin 0.23µg/ml and deltamethrin 0.21µg/ml mostly samples were polluted with cypermethrin, deltamethrin, permethrin and bifenthrin [26]. In the present study chlorpyrios residue was found in 3 samples of District Astore the highest residue level was 0.01mg/kg found in Eidgah4 and the lowest is 0.002mg/kg in Fina. Only 2 samples from Gilgit were detected with the value of 0.019 mg/kg and 0.012mg/kg in Danyore. A study was conducted to investigate OCPs, OPs, Pyrethroids, and carbamate residues in human and cow milk. Hexachlorobenzene, p, p'-dicofol, and chlorpyrifos were found in all samples [27]. Shangi*et al.*, [28] studied the presence of isomers of HGH, chlorpyrifos, Malathion and methyl-parathion was monitored in human milk from Bhopal, Madhya Pradesh. The concentration of endosulfan was highest and the concentrations of chlorpyrifos and Malathion were 3.5, 1.5, and 8.4 fold.

According to the study was conducted to investigate the relation between pesticides contamination of feedstuffs and residues in bovine milk, chlorpyrifos is the main contaminant with a residue level of 6.01in feedstuff and 2.58ng/g in milk samples. Other pesticide residues observed in feed and milk samplesendosulphansulphate, cypermethrin,

DDE, lindane, Malathion and fenvalerate. The main source of pesticide residue in milk is the feedstuff on that animal's feed [29]. The milk samples were analyzed for pesticide residues of chlorpyrios, endosulfan, profenofs, and bifenthrin. The residues in raw and ultra-heated milk were determined between the rangeof 0.1-30µg/g. Residues in heat-treated samples were within the range of 0.1-30µg/L. All UTH processed samples contain pesticide residue within the acceptable limit set by the (WHO) on the other hand raw milk samples, chlorpyrios and endosulfan were found above the maximum residue limit (MRL), raw milk samples show a higher prevalence than heat-treated samples [30].

Conclusion.

It is concluded that the pesticide residues were found magnificently in the mother milk of Danyore, Gilgit and Eidgah, Astore. Mostly detected pesticides in mothers milk were found fromfruits and vegetables exported from urban areas of Pakistan, and use of pesticides and synthetic fertilizers to their fields extensively. The multiparous women had prominent pesticide residues than primiparas. Among the analyzed pesticides the residue of cypermethrin, Deltamethrin and Chlorpyrifos was present in some of the samples. The lactating mothers were mainly consuming vegetables and fruits imported from urban areas during the gestation period and after delivery. Although the residue level was low in all samples if preventive measures are not taken by people and the government it would be a threat to human health in future.

Author's Contribution. This study was designed and directed by S. urooj and M.A.NAfees as principal investigators. Saif-Ud-Din provided all the technical and experimental Guidance. S.Ali and Saif-Ud-Din performed and participated in Statistical analysis and preparation of the manuscript draft.

Conflict of interest. No conflict of interest is associated with this publication among Authors.

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Heart Attack Risk Prediction with Duke Treadmill Score with Symptoms using Data Mining

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The healthcare industry has a huge volume of patients' health records but the discovery of hidden information using data mining techniques is missing. Data mining and its algorithm can help in this situation. This study aims to discover the hidden pattern from symptoms to detect early Stress Echocardiography before using Exercise Tolerance Test (ETT). During this study, raw ETT data of 776 patients are obtained from private heart clinic "The Heart Center Bahawalpur", Bahawalpur, South Punjab, Pakistan. Duke treadmill score (DTS) is an output of ETT which classifies a patient's heart is working normally or abnormally. In this work multiple machine learning algorithms like Support Vector Machine (SVM), Logistic Regression (LR), J.48, and Random Forest (RF) are used to classify patients' hearts working normally or not using general information about a patient like a gender, age, body surface area (BSA), body mass index (BMI), blood pressure (BP) Systolic, BP Diastolic, etc. along with risk factors information like Diabetes Mellitus, Family History, Hypertension, Obesity, Old Age, Post-Menopausal, Smoker, Chest Pain and Shortness Of Breath (SOB). During this study, it is observed that the best accuracy of 85.16% is achieved using the Logistic Regression algorithm using the split percentage of 60-40.
Keywords: Duke Treadmill Score, Data Mining, ETT, Support Vector Machine, Logistic Regression, J.48, Random Forest, WEKA

INTRODUCTION

The Healthcare industry collects a large volume of data that needs to be mined to discover useful information for better decision making. Heart Disease is the major cause of mortality worldwide. Symptoms have a huge impact on heart disease. Some are more important and some are less. It is very important to detect the weightage of each attribute. More weighted symptoms have a high impact on disease prediction. For these reasons we are using data mining to check which attribute has more weightage to detect the duke treadmill score which is directly associated with heart attack chances[1]

Data mining helps to reduce the number of tests and early prediction of disease and avoid highly charged test costs and time to start treatment of a patient. Heart disease early prediction system is useful for medical experts and policymakers to avoid mortality with early treatment start based on symptoms. This paper presents the model and symptoms that help diagnose the patient's condition.

Site Map

This study was conducted in Bahawalpur, Southern Punjab, Pakistan in the Faculty of Computing, The Islamia University of Bahawalpur, Bahawalpur.

Figure 1. Study Site

LITERATURE REVIEW

Data mining and algorithms used in medical domain

Data mining was helpful in previous heart disease prediction systems[2, 3]. Logistic Regression, Support Vector Machine, J.48, KNN, K-Nearest, and Decision Table are powerful classification algorithms used to classify heart disease[4]. These algorithms are used to process the raw data and make some useful relationships between different attributes in data.

Early study on Prediction of Duke Treadmill score

Duke Treadmill Score (DTS) is a value that calculates from the exercise time, Angina Score, and ST Deviation[5]. DTS calculate with the following formula: exercise time − (5 × maximum ST deviation) − (4 × angina index). This formula generates an integer number that is further divided into categories. If the DTS value is greater than or equal to 5 then it considers as normal and if the value is less than 5 and greater than or equal to -10 then it considers as Moderate Risk for the patient and if the DTS value is below then -10 then it considers as High Risk for the patient. These exercise values come from exercises that are based on some protocol like Bruce, Modified Bruce or Naugton, etc. Some previous studies were done using DTS and other medical test results with data mining [6] which is used to predict different coronary arteries disease.

In this study, the duke treadmill score was categorized into two categories either normal or abnormal as shown in **Table 1**

Table 1. Duke Treadmill Score Categories

Sr.	Duke Treadmill Score	Category
1	>=5	Normal
2	<5	Abnormal

PROBLEM STATEMENT

Previously there are many reported research is presented on Duke Treadmill Score (DTS) but this test is difficult for everyone to achieve the standard of its protocol. Old age patients and kids who are not able to walk on the treadmill at a specific time to achieve targeted heart rate. In this work we are predicting patients' heart condition as normal or abnormal without performing ETT and calculating DTS.

MATERIALAND METHODS

1. Data Set

Dataset used in this study is constructed from patients' ETT data provided by Dr. Zafar Iqbal Jam (Cardiologist), The Heart Center Bahawalpur, Punjab, Pakistan. There were 776 patients' data from the year 2016 to 2021. In this dataset, there are 15 attributes and each patient is classified as having normal or abnormal heart activity based on duke score. This data set contains 157 females and 619 male patients while their male patients' age is from 18 to 75 years and female patients' age is 26 to 72 years. Male patient's BSA has range from 1.13 to 2.92 and in female patients' BSAis from 1.29 to 2.49.Male patient's BMI has ranged from 16.30 to 341.16 and in female patients it is 15.22 to 206.59. Two attributes are Blood Pressure Systolic from 90 to 180 and Blood Pressure Diastolic from 52 to 110. After these attributes of our dataset, nine attributes are risk factors in patients. Their statistics are as follows: Diabetes Mellitus is one of the major issues these days[7].

A total of 144 patients has this risk factor where 104 are male patients and 40 are female patients. Family history is another risk factor in patients which indicates that other family members have heart problems. In this dataset, 136 patients have a family history of CHD where 105 are male patients and 31 female patients. Next, the Hypertension risk factor has in 335 patients where 239 patients are male and 96 patients are female. Hypertension is more common in old age people. Mortality in heart patients has increased due to hypertension[8]. The next risk factor of this dataset is obesity. There are 169 obese patients in a dataset where 116 are male and 53 are female. The next risk factor in this dataset is Old Age. Patients with an old age risk factor are 74 where 56 are male patients and 18 are female patients. Attribute Old age decided by the doctor.

A patient has any heart problem due to age factor considered as an Old Age risk factor. The next risk factor is Smoking. Smoking has dangerous side effects on heart patients. There are a lot of previous researches that prove that smoking is a serious cause and risk factor for heart patients[9]. 152 patients are smokers where 151 patients are male patients and only one patient is a female smoker. The next risk factor is Post-menopausal. There is 19 patient with this risk factor all are females. The next attribute is Chest pain, a total of 708 patients have a primary indication of chest pain where 566 are male patients and 142 are female patients. Chest pain is the primary indication of CHD. A lot of studies have been conducted to prove the chest pain is an indication of CHD[10, 11]. Shortness of Breath (SOB) is a condition of

the patient when he/she run or even walks sometimes and starts a problem in breathing. But some are severe cases where patients start shortness of breath by just walking some steps and sitting up and down[12]. 13 patients have SOB where 9 are male patients and 4 are female patients.

Table 2. Data Set Attributes

Sr.	Attribute	Description	Total	Division
1	Gender	Gender attribute represent the Sex either male or female 1=Male 0=Female	776	**619-Male, 157-Female**
2	Age	Age is number in years	776	**Male(18-75), Female (26-72)**
3	BSA	BSA is Body surface area.[13]	776	**Male (1.13-2.92), Female (1.29-2.49)**
4	BMI	Body mass Index [14]	776	**Male (16.30-341.16), Female (15.22-206.59)**
5	BP Systolic	Blood pressure systolic.	776	**Male (90-179), Female (92-180)**
6	BP Diastolic	Blood pressure Diastolic.	776	**Male (52-110), Female (53-108)**
7	Diabetes Mellitus	Diabetes Mellitus normaly called diabeted. 1= Diabetes Mellitus 0= No DM	144	**Male=104, Female=40**
8	Family History	Family history means any heart disease patients in parents or grandparents. 1= Family Has History 0=No Risk of family.	136	**Male=105, Female=31**
9	Hypertension	Hypertension means high blood pressure. 1=Patient has hypertension 0= patient does not have hypertension	335	**Male=239, Female=96**
10	Obesity	Obesity means patient has more weight then normal 1=Patient has obesity RF 0=Patient does not have RF of obesity	169	**Male=116, Female=53**
11	Old Age	Patient's age is above 50-years consider as an old age patient. 1= Patient is old age. 0= Patient is not old age.	74	**Male=56, Female=18**
12	Post-menopausal	Post-menopausal is a risk factor for females 1=Patient has PM risk factor. 0=Patient has not risk factor of PM.	19	**Male=0, Female=19**

13	Smoker	Patient has smoking habit is called smoker. 1= Smoker 0= Not Smoker	152	**Male=151, Female=1**
14	Cheast Pain	Cheast pain has all type of cheast pain either cardic or non cardic. 1= Patient has Cheast pain. 0= Patient doest not have Cheast pain.	708	**Male=566, Female=142**
15	SOB	Shortness of breath. 1= Shortness in breath 0= Patient has no shortness in breath.	13	**Male=9, Female=4**

Data Preparation

In this study, for experiments purpose WEKA version 3.8.2 is used. Duke score for each patient is shown in histogram Figure 2. Duke Score already discussed in **Early study on Prediction of Duke Treadmill score**.

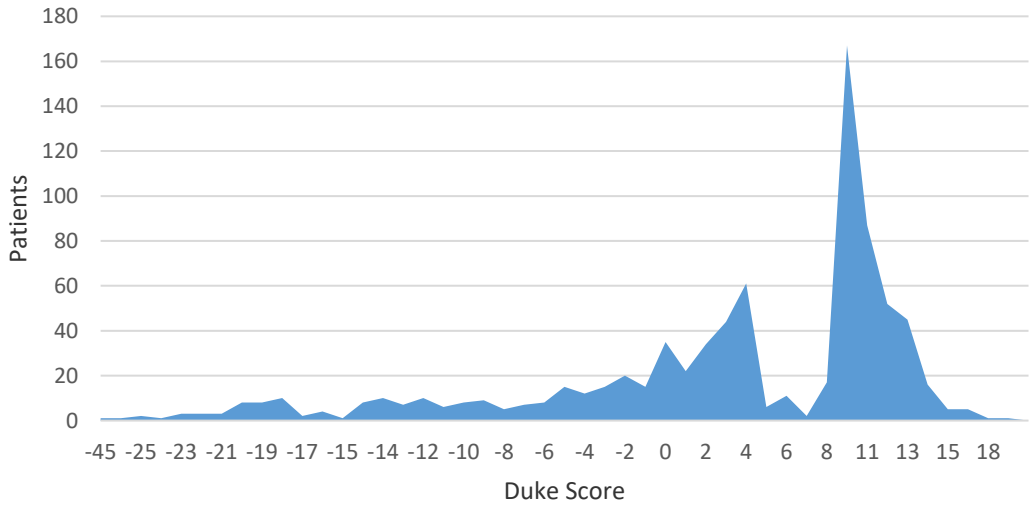

Figure 2.Distribution of patients by DTS

The patients' data were collected by the Doctor mentioned in **Data Set** section in his medical clinic. Each patient is classified as having a normal or abnormal heart condition based on the Duke results obtained by ETT examination. During ETT a patient has to walk on the treadmill using according to certain protocols as discussed in **Early study on Prediction of Duke Treadmill score**.

During ETT a patient is required to achieve some specific heart rates, blood pressures, etc. are monitored. Initially, the provided data was in SQL format where a few columns contain multi-value attributes like risk factors and primary indications. These columns are normalized by spreading these into multiple columns. Furthermore, the data is

manually observed and a few columns with less than 15 occurrences in a complete column are removed. All the columns for risk factors and primary indicators are in binary form. The data is labeled manually into two classes which are normal and abnormal based on samples' duke score. The samples having equal or more than 5 duke scores are labeled normal else labeled abnormal.

By using the above mansion risk factors and primary indications we want to predict patients' heart condition before performing ETT. In terms of this prediction, we are using WEKA's Algorithms.

- Logistic Regression Algorithm, Logistic regression is a classifier with binary classification technique. Logistic Regression is a formula that came from statistics. It is like linear regression. It works with binary values based on some specified set of dependent or independent variables[15, 16].
- Random Forest Algorithm, Random forest is rapidly used and helpful in previous studies for decision making. Yeshvendra K. Singh uses this algorithm to predict Heart Disease with 85% correct prediction [17, 18].
- J.48 Algorithm, J.48 is a famous classifier for data mining. J.48 used in many previous studies to predict heart disease and some other diseases using symptoms of data[19, 20].
- SVM, a Support vector machine (SVM) is another powerful tool for using classification and regression. This algorithm is also used to analyze data and pattern recognition. SVM is a mathematical function for creating a model for real-world data. This is already proved by Mythili T. in [21] and Chandra Babu Gokulnath in [22] with the highest accuracy of SVM being 83% in his study.

RESULTS

Cross-Validation and Percentage Split was used for each algorithm discussed separately with these strategies.

LOGISTIC REGRESSION

Firstly Logistic regression was used to analyze and classify algorithms using WEKA. Initially, Logistic regression was applied with no filter with split data of 60% as training data and 40% as test data. With this algorithm total, 129 patients were correctly identified as normal while 20 patients were normal but identified as abnormal patients. Same as with abnormal patients, 135 patients were correctly identified as abnormal similarly, 26 patients were abnormal but identified as normal patients. With this algorithm, 264 patients were correctly identified out of 310 patients which were tested. The overall accuracy for this algorithm is 85.16%. Detail about the algorithm classification is given below in **Table 3**.

This classifier showed the accuracy of both classes' values Normal and Abnormal. Normal Accuracy was 86.6% and abnormal accuracy was 83.9%. Detail accuracy of this algorithm is shown in the below **Table 3**.

Table 3. Logistic Results of Percentage Split

	Detailed Accuracy By Class				
	Precision	**Recall**	**F-Measure**	**MCC**	**ROC Area**
Normal	83.20%	86.60%	84.90%	70.40%	89.70%
Abnormal	87.10%	83.90%	85.40%	70.40%	89.70%

The logistic algorithm was again applied with cross-validation with 10-Fold. With this algorithm total, 306 patients were correctly identified as normal but 73 patients were normal but identified as abnormal patients. Same as with abnormal patients, 320 patients were correctly identified as abnormal but actually 77 patients were abnormal but identified as normal patients. With this algorithm, 626 patients were correctly identified out of 776 patients' data. The overall accuracy for this algorithm is 80.67%. Detail about the algorithm classification in below **Table 4**.

This classifier showed the accuracy of both class values Normal and Abnormal. Normal Accuracy is 80.70% and abnormal accuracy is 80.60%. Detail accuracy of this algorithm is shown in the below **Table 4**.

Table 4. Logistic Results Of Cross Validation

	Detailed Accuracy By Class				
	Precision	**Recall**	**F-Measure**	**MCC**	**ROC Area**
Normal	79.90%	80.70%	80.30%	61.30%	89.30%
Abnormal	81.40%	80.60%	81.00%	61.30%	89.30%

RANDOM FOREST

The second algorithm used for classification is Random Forest. Initially, Random Forest was applied with no filter and split data of 60% as training data and 40% as test data. With this algorithm total of 122 patients were correctly identified as normal but 27 patients were normal but identified as abnormal patients. Similarly, 137 patients were correctly identified as abnormal but 24 patients were identified as normal patients which were actually abnormal. With this algorithm, 259 patients were correctly identified out of 310 patients' test data. The overall accuracy for this algorithm was up to 83.55%. Detail about the algorithm classification is **Table 5**.

This classifier shows the accuracy of both classes' values Normal and Abnormal. Normal Accuracy was 81.90% and abnormal accuracy was 85.10%. Detail accuracy of this algorithm is shown in the below **Table 5**

Table 5. Random Forest Results of Split Percentage

	Detailed Accuracy By Class				
	Precision	**Recall**	**F-Measure**	**MCC**	**ROC Area**
Normal	83.60%	81.90%	82.70%	67.00%	89.20%
Abnormal	83.50%	85.10%	84.30%	67.00%	89.20%

Random Forest algorithm was again applied with cross-validation with 10-Fold. With this algorithm total of 296 patients were correctly identified as normal but 83 patients were normal which were identified as abnormal patients. Same as with abnormal patients, 331 patients were correctly identified as abnormal indeed 66 patients were abnormal but identified as normal patients. With this algorithm, 627 patients were correctly identified out of 776 patients' data. The overall accuracy for this algorithm was obtained up to 80.80%. Detail about the algorithm classification is in **Table 6**.

This classifier showed the accuracy of both classes' values Normal and Abnormal. Normal Accuracy was 78.10% and abnormal accuracy was 83.40%. Detail accuracy of this algorithm is shown in the **Table 6.**

Table 6. Random Forest Results With Cross Validation

Detailed Accuracy By Class

	Precision	Recall	F-Measure	MCC	ROC Area
Normal	81.80%	78.10%	79.90%	61.60%	89.00%
Abnormal	80.00%	83.40%	81.60%	61.60%	89.00%

J.48

The third algorithm used for classification was J.48. Initially, J.48 was applied with no filter and split data of 40% as training data and 60% as test data. With this algorithm total of 189 patients were correctly identified as normal but 46 patients were normal but identified as abnormal patients. Similarly, 175 patients were correctly identified as abnormal but 56 patients were abnormal but identified as normal patients. With this algorithm, 364 patients were correctly identified out of 466 patients' test data. The overall accuracy for this algorithm was 78.11%. Detail about the algorithm classification in below **Table 7**.

This classifier showed the accuracy of both classes' values Normal and Abnormal. Normal Accuracy was 80.40% and abnormal accuracy was 75.80%. Detailed accuracy of this algorithm is shown in the below **Table 7**.

Table 7.J.48 Results with Split Percentage

Detailed Accuracy By Class					
	Precision	**Recall**	**F-Measure**	**MCC**	**ROC Area**
Normal	77.10%	80.40%	78.80%	56.30%	79.90%
Abnormal	79.20%	75.80%	77.40%	56.30%	79.90%

J.48 algorithm was again applied with cross-validation 15-Folds. With this algorithm total, 295 patients were correctly identified as normal but 84 patients were normal but identified as abnormal patients. Same as with abnormal patients, 315 patients were correctly identified as abnormal but 82 patients were abnormal but identified as normal patients. With this algorithm, 610 patients were correctly identified out of 776 patients' data. The overall accuracy for this algorithm is 78.61%. Detail about the algorithm classification in below **Table 8**.

This classifier shows the accuracy of both class values Normal and Abnormal. Normal Accuracy is 77.80% and abnormal accuracy is 79.30%. Detail accuracy of this algorithm is shown in the below **Table 8**

Table 8.J.48 Results With Cross Validation

Detailed Accuracy By Class					
	Precision	**Recall**	**F-Measure**	**MCC**	**ROC Area**
Normal	78.20%	77.80%	78.00%	57.20%	79.90%
Abnormal	78.90%	79.30%	79.10%	57.20%	79.90%

SUPPORT VECTOR MACHINE

The last algorithm used for classification was SVM. Initially, SVM was applied with no filter and split data of 40% as training data and 60% as test data. With this algorithm total, 127 patients were correctly identified as normal but 22 patients were normal but identified as an abnormal patient. Same as with abnormal patients, 128 patients were correctly identified as abnormal but 33 patients were abnormal but identified as normal patients. With this algorithm, 255 patients were correctly identified out of 310 patients' data. The overall accuracy for this algorithm was up to 82.26%. Detail about the algorithm classification in below **Table 9**.

This classifier shows the accuracy of both class values Normal and Abnormal. Normal Accuracy was 85.20% and abnormal accuracy was 79.50%. Detail accuracy of this algorithm is shown in the **Table 9**

Table 9. SVM Result with Split Percentage

Detailed Accuracy By Class					
	Precision	**Recall**	**F-Measure**	**MCC**	**ROC Area**
Normal	79.40%	85.20%	82.20%	64.70%	82.40%
Abnormal	85.30%	79.50%	82.30%	64.70%	82.40%

SVM algorithm was again applied with cross-validation 5-Folds and random seed 2 from detail settings. With this algorithm total of 310 patients were correctly identified as normal but 69 patients were normal but identified as abnormal patients. Same as with abnormal patients, 314 patients were correctly identified as abnormal but 83 patients were abnormal but identified as normal patients. With this algorithm, 624 patients were correctly identified out of 776 patients' data. The overall accuracy for this algorithm is up to 80.41%. Detail about the algorithm classification is given in **Table 10**

This classifier shows the accuracy of both class values Normal and Abnormal. Normal Accuracy abnormal accuracy was 81.80% and 79.10% respectively. Detail accuracy of this algorithm was shown in the below **Table 10**

Table 10.SVM Results with Cross Validation

Detailed Accuracy By Class					
	Precision	**Recall**	**F-Measure**	**MCC**	**ROC Area**
Normal	78.90%	81.80%	80.30%	60.90%	80.40%
Abnormal	82.00%	79.10%	80.50%	60.90%	80.40%

1. DISCUSSIONS

After applying all the algorithms one by one with both Split Percentage in **Table 11**and Cross-validation in **Table 12**, we had the best performance of each algorithm. The highest performance originated from Logistic Regression Algorithm with a split percentage, which was 85.16% overall. We compared all results into summarized form.

Table 11. Split Percentage of Each Algorithm

Detailed Accuracy By Algorithm (All values are in %)						
	Overall Accuracy	**Precision**	**Recall**	**F-Measure**	**MCC**	**ROC Area**
LR	***85.16***	***85.20***	***85.20***	***85.20***	***70.40***	***89.70***
RF	83.55	83.50	83.50	83.50	67.00	89.20
J.48	78.11	78.20	78.10	78.10	56.30	79.90
SVM	82.26	82.50	82.30	82.30	64.70	82.40

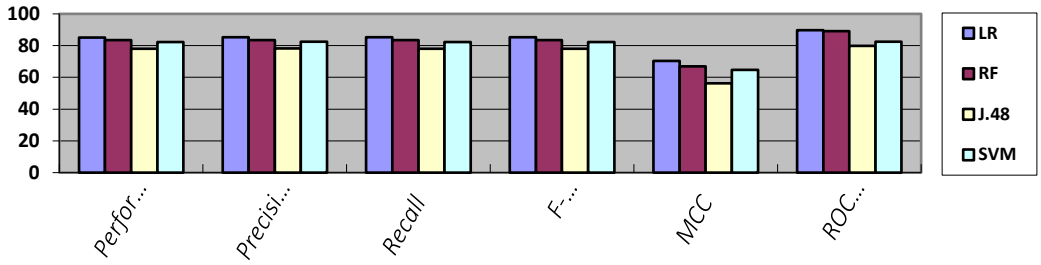

Figure 3. Results accuracy of each algorithm with split percentage

Table 12. Cross Validation of Each Algorithm

Detailed Accuracy By Algorithm (All values are in %)						
	Overall Accuracy	**Precision**	**Recall**	**F-Measure**	**MCC**	**ROC Area**
LR	80.67	80.70	80.70	80.70	61.30	89.30
RF	80.80	80.80	80.80	80.80	61.60	89.00
J.48	78.61	78.60	78.60	78.60	57.20	79.90
SVM	80.41	80.50	80.40	80.40	60.90	80.40

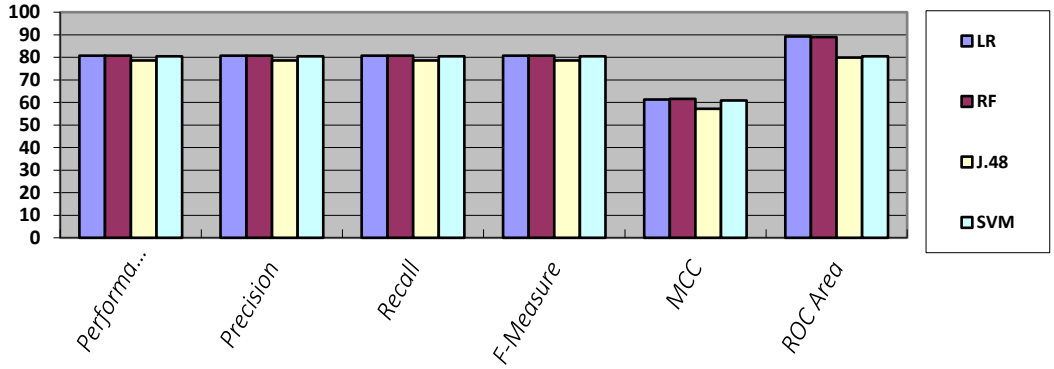

Figure 4. Results accuracy of each algorithm with cross validation

Table 13 and **Table 14** shows statistical results of used algorithms. According to these LR with split percentage showed maximum agreement of 0.7. The results were in accordance with the previous results.

Table 13. Algorithm results with split percentage results

Algorithm Stats With Split Percentage Results		
	Kappa Statistic	**Mean Absolute Error**
LR	0.7032	0.2501
RF	0.6702	0.2778
J.48	0.562	0.2627
SVM	0.6456	0.1774

Table 14. Algorithm results with cross validation results

Algorithm Stats With Cross Validation Results		
	Kappa Statistic	**Mean Absolute Error**
LR	0.6133	0.2594
RF	0.6154	0.2732

J.48	0.5719	0.2647
SVM	0.6084	0.1959

2. CONCLUSION & FUTURE WORK

Results showed that LR Algorithm can correctly predict the patient condition up to 85% accuracy. To date, this is the first study to predict patients' heart condition using their general condition and symptoms without performing ETT and calculating DTS. In future work, we will try to improve accuracy by adding more features to the dataset. Patients with an abnormal heart condition can be further classified into moderate and high-risk patients.

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Activity Detection of Elderly People Using Smartphone Accelerometer and Machine Learning Methods

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Elderly activity detection is one of the significant applications in machine learning. A supportive lifestyle can help older people with their daily activities to live their lives easier. But the current system is ineffective, expensive, and impossible to implement. Efficient and cost-effective modern systems are needed to address the problems of aged people and enable them to adopt effective strategies. Though smartphones are easily accessible nowadays, thus a portable and energy-efficient system can be developed using the available resources. This paper is supposed to establish elderly people's activity detection based on available resources in terms of robustness, privacy, and cost-effectiveness. We formulated a private dataset by capturing seven activities, including working, standing, walking, and talking, etc. Furthermore, we performed various preprocessing techniques such as activity labeling, class balancing, and concerning the number of instances. The proposed system describes how to identify and classify the daily activities of older people using a smartphone accelerometer to predict future activities. Experimental results indicate that the highest accuracy rate of 93.16% has been achieved by using the J48 Decision Tree algorithm. Apart from the proposed method, we analyzed the results by using various classifiers such as Naïve Bays (NB), Random Forest (RF), and Multilayer Perceptron (MLP). In the future, various other human activities like opening and closing the door, watching TV, and sleeping can also be considered for the evaluation of the proposed model.
Keywords: Machine Learning; Activity Detection; Elderly-People; Activity Recognition, and Accelerometer.

INTRODUCTION

Machine learning has become a very active research topic nowadays. The goal of machine learning is to improve computer programs. These programs expand themselves when new data arrives and may teach it to change. Multiple applications for machine learning are available such as face detection, face reorganization, image classifications, voice

reorganization, etc. Smartphones have become popular all over the world with several integrated sensors. Smartphones have a wide range of sensors to record human interaction with our surroundings [1].Therefore, these devices assist in human activity recognition (HAR) [2].The increasing usage of smart home technologies, combined with machine learning techniques, can provide valuable insights into people's behavior [3]. Human activity recognition (HAR) through sensors embedded in smartphones has allowed for the development of systems that are capable of detecting and monitoring human behavior [4]. The number of elderly people is increasing rapidly day-by-day and taking excellent care of them is becoming an enormous issue not only in developing countries but also in developed countries. Elderly people have some health issues that have to be resolved. Diabetes mellitus (DM) is the most common and serious chronic disease in the United States [7]. Many adults use drugs to manage chronic conditions such as heart disease, lung disease, arthritis, pain, and depression [8]. Human activity detection within smart homes is one of the bases of unobtrusive wellness monitoring of a rapidly aging population in developed countries [9].

Activity classification is a recent concept involving the use of technology to automatically recognize different activities and, in some cases, to collate this information into a continuous record [10].Detection of adults' activities is a crucial task in the life of an adult because in this period of age, mostly old persons suffer due to some kind of disease and they need a caretaker for their health caring but in this modern and speedy age no one has much time to take care of an old one and cannot spare the whole day for this purpose. If the caretaker has a mechanism to alarm the time of the disaster, he can easily come near an old one, and take him to a hospital or take care of him during any critical situation. The use of dependencies can lead to elegant and well-performing models when a process is well understood [11]. Rapidly developing technology has made mobile and wireless devices part of daily life [12]. Machine learning techniques have widely been used to detect human activities but they mostly require infrastructure support, for example, installation of video cameras in the monitoring areas and the use of cameras is not the best technique in some cases, and some places, for example, bathroom camera is not good to capture the action of an old person. Smartphones can be used for Human Activity Recognition (HAR) through continuous monitoring of ADLs (Activity of daily life) [15, 18].

In our research work, we proposed a system using machine learning that detects the movement of elderly people using a smartphone accelerometer dataset. It will become a product which will be beneficial for elder people and very economical because we use the available resources to get data of elderly people. We are becoming statistics of aged people with the aid of the use of a cell phone accelerometer [19, 20], that is in their front pocket. Dataset has three axes, x, y, and z [16]. The x-axis represents the horizontal movement, the y-axis represents vertical movement, and the z-axis represents diagonal movement. After getting datasets, we processed the data and formulated it in a form in which many classifiers could be applied like: activity labeling, class balancing, and reducing the number of instances from huge data. Seven different activities can be detected. Different classifiers were applied on processed data, j48, nave based, MLP, and RF. By analyzing the dataset, results will be generated in the result set. The results of different activities are combined, and the maximum average accuracy of 93.16 is achieved through the Decision Tree J48 algorithm.

LITERATURE REVIEW

Activity detection of elderly people has gained worldwide attention over the last few years. There has been a lot of work done on early activity detection of elderly people using manual techniques. This study aims at activity detection of elderly people using machine learning algorithms. Sri Harsh et al. [1] perform analysis on smartphone data set by using machine learning algorithms. Some algorithm generates maximum accuracy in some kind of activities. Le et al. [2] work on fall detection by using mobile phone accelerometer data set, applying a random forest algorithm to get maximum accuracy. Kouta, et al. [3] detect the activities of elderly people by using the Internet of Things sensor and combining the classification and regression approaches. Montero Quispe et al. [4] work on mobile phone embedded sensor data and apply classification algorithm MBOSS, reduce the complexity of the computational process and generate features automatically. Anguita, et al. [5] used an SVM classification algorithm on mobile phone sensor data in the health care domain. Ravi, N et al. [6] distinguished in different activities to detect with the use of single accelerometer by mounted on the body of human being. And explain that short activities can be detected easily like opening and closing doors, etc. Chatterjee et al. build a monitoring system to track the activities of elderly people suffering from diabetes [7]. Wang et al. designed a model for elderly people to be aware of the current situation [8].

Ni et al. [9] describe the Elderly's Independent Living in Smart Homes, several activities, and sensor based infrastructure surveys to provide Services. Assist to enhance the quality of life, prolong independent living and reduce caretaker's time and minimize the healthcare cast in general, without losing the safety that continuous and unobtrusive monitoring provides. Preece et al. [10] explain their work in two phases, in the first one extract the feature of sensor date worn on the body, and the second phase applies advanced classification on data. Kasteren et al. [11] designed a wireless sensor network to detect the activities of elderly people applying the Morkv Model to recognize the number of activities. In the work of Özdemir, A. T., and Darshan, B. [12] machine learning techniques are used to recognize fall detection with wearable sensors. In elderly people fall is an area very risky factor in the health care domain. Vavoulas et al. [13] used a mobile phone accelerometer to get data and preprocess that data to detect falls and make a fall detection algorithm. Body-mounted and wearable devices are available to get data from elderly people. Casale et al. [14] perform a comparative study on the wearable accelerometer dataset and extract different features to apply a random forest classifier. Zia et al. [15] apply different classifiers on smartphone accelerometer data set to detect Activity of daily life and fall. Sayem et al. [16] used smartphone accelerometer data set to detect nursing activities, apply SVM, Random forest classifier to get maximum accuracy.

Mekruksavanich, S., and Jitpattanakul developed LSTM based framework to detect human activities [17]. They used a tri axes accelerometer and a tri-axis gyroscope for data gathering. Kadhum et al. [18] get the records by using a phone accelerometer and gyroscope records set to carry out extraordinary gadget learning algorithms to hit upon falls, the follow neural community, and SVM via the usage of WEKA tool. Bayat et al. [19] used the accelerometer records set of the phone positioned in a pent pocket to get the facts set and perform preprocessing on information and integrate three distinctive classifier effects. Another work on activity detection of elderly people was performed by Porwal et al. [20] to

preprocess the smartphone data to detect human activities by using machine learning techniques.

Though, there are a significant amount of work has been done previously. The accurate detection of elderly people's activities is a challenging problem. The proposed method employed machine learning-based methods such as decision tree, naïve bays, random forest, and multilayer perceptron for elderly people's activity detection in order to assist them for a better quality of life.

MATERIAL AND METHODS

We used datasets to evaluate our primary model. We used the smartphone accelerometer to get the reading of three different axes. The smartphone is located in the front pocket of a person. To collect data, we used a tri-axial accelerometer in the Android phone to measure acceleration. Data from this smartphone accelerometer includes the acceleration along the x-axis, y-axis, and z-axis [14]. The X-axis represents the horizontal/sideways movement of the user (x-axis), the y-axis represents vertical movement upward/downward, and the z-axis represents diagonal movement. The activity Detection system cannot perform the classification task directly on raw acceleration data. Generally, the classification will be performed after an informative data representation is created in terms of feature vectors as depicted in Figure 1.

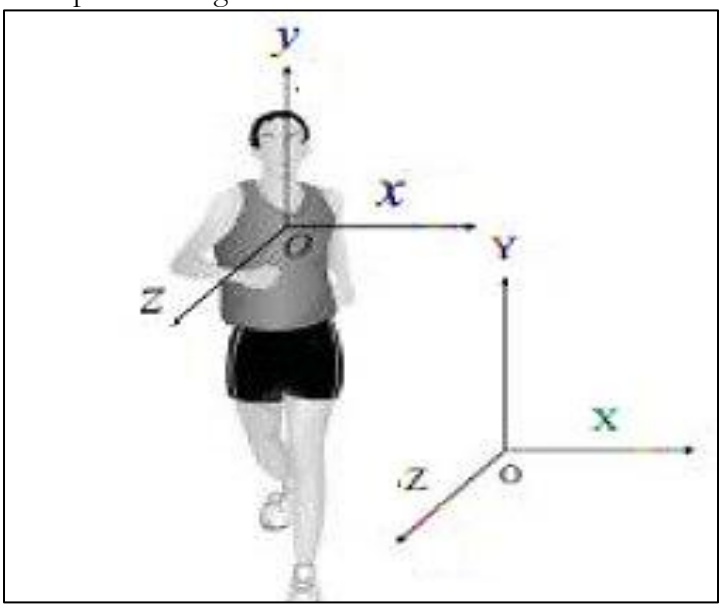


Figure 1. Dataset Directions

The schematic of the proposed framework is given in Figure 2. The overall framework comprised dataset gathering, preprocessing, feature extraction, and classification of seven activities. These phases are explained in the underlying section.

Labeling activity: J48 algorithm cannot perform on numeric data but in accelerometer dataset the consist on numeric data there are three attributes and one class in the dataset so the class consist on number activities detected against the attributes and activities were in numeric values like one, two, etc. we labeled the number of Activities by replacing the

numbers to A, B, C, D, E, F, and G. So, number of activities labeled as an alphabetic type of data in Table 1.

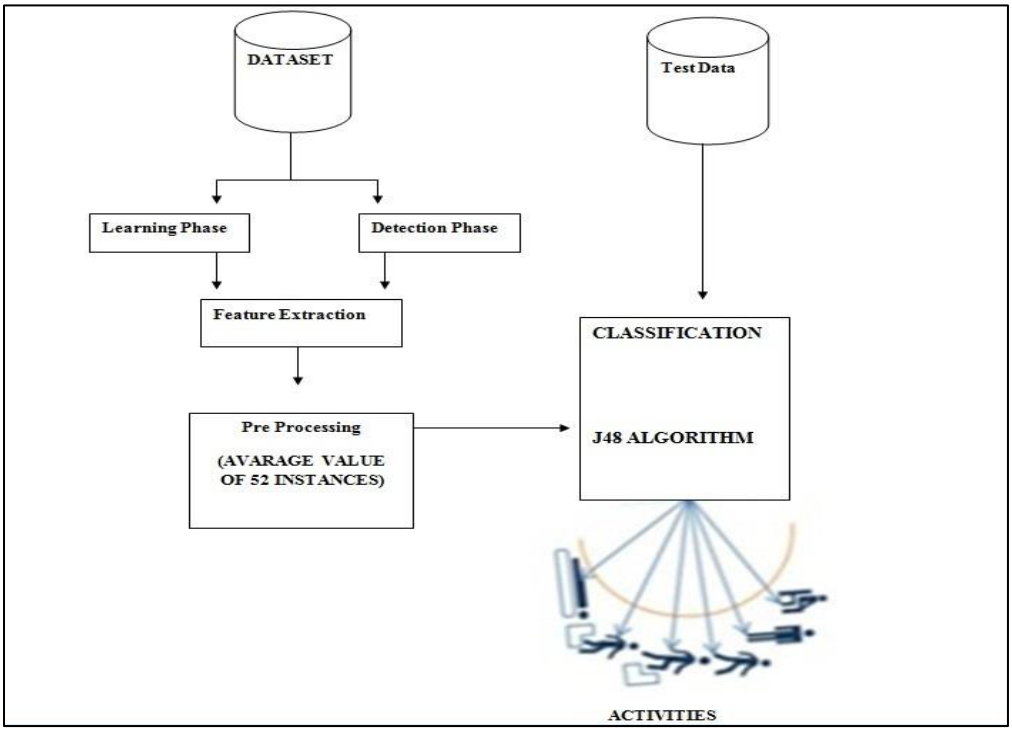


Figure 2. The architecture of the proposed Model for Activity Detection of Elderly People

Dataset: We collected a dataset from a Smartphone accelerometer placed in the front pocket. The dataset is collected from 15 participants performing 7 activities as shown in Table 1.

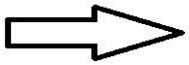
Table 1. Activity Labeling

Sr. No	Label	Activity
1	A	Working on Computer
2	B	Stand Up, Walking
3	C	Standing
4	D	Walking
5	E	Going up and down Stairs
6	F	Walking and Talking
7	G	Talking and Standing

Class Balancing: In the accelerometer dataset, the number of instances of one class is very high from other class, therefore, classification cannot work on this kind of dataset, then we performed the procedure of class balancing on the data set and separated the number of

activities one by one in a single file of a class number of instances of this class named as 'YES' and the same quantity of instances of other class are named as'NO'. Imbalance data is not good for different kinds of classification algorithms, and data balancing is used to overcome this problem. The tabular representation of class balancing is shown in Figure 3.

X Axis	Y Axis	Z Axis	Activity
1607	1910	1910	A
1546	2045	1910	A
1529	2049	1972	A
1859	2376	2076	B
1849	2374	2077	B
1859	2381	2074	B
1907	2383	2039	C
1908	2387	2032	C
1907	2391	2034	C
1856	2403	2066	D
1887	2353	2043	D
1887	2327	2019	D
1966	2350	2082	E
1956	2354	2071	E
1953	2353	2068	E
1914	2311	1986	F
1909	2311	1988	F
1917	2317	2005	F
1931	2386	2073	G
1926	2382	2072	G
1927	2388	2074	G



X Axis	Y Axis	Z Axis	Activity
1599	2002	2004	YES
1627	2099	2066	YES
1883	2265	1847	YES
2101	2324	2010	YES
1960	2356	2193	YES
1966	2359	2114	YES
1952	2391	2051	YES
1953	2379	2108	YES
1958	2374	2124	YES
1963	2374	2129	YES
1879	2381	1986	NO
1877	2380	1986	NO
1876	2380	1986	NO
1876	2380	1987	NO
1876	2381	1987	NO
1876	2380	1990	NO
1872	2379	1978	NO
1873	2380	1980	NO
1873	2378	1981	NO

Figure 3. Class Balancing

There are many existing mechanisms for activity detection systems, but the major issues are the security and accuracy of the system. To improve the problem of accuracy and the efficiency of the system, a very common classification approach i.e. J48 is employed in our study. Proposed research work introduces a framework to develop a classifier based on data mining techniques. The testing procedure is performed on the publicly available Weka Tool by using the Decision Tree J48 algorithm. The experimental results and visualization tree is given in Figure 4, and Figure 5, respectively.

```
=== Summary ===

Correctly Classified Instances         101               96.1905 %
Incorrectly Classified Instances         4                3.8095 %
Kappa statistic                          0.9235
Mean absolute error                      0.0495
Root mean squared error                  0.1944
Relative absolute error                  9.9117 %
Root relative squared error             38.9026 %
Total Number of Instances              105

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.982    0.060    0.947      0.982    0.964      0.924    0.970     0.955     YES
                 0.940    0.018    0.979      0.940    0.959      0.924    0.970     0.960     NO
Weighted Avg.    0.962    0.040    0.963      0.962    0.962      0.924    0.970     0.957

=== Confusion Matrix ===

  a  b   <-- classified as
 54  1 |  a = YES
  3 47 |  b = NO
```

Figure 4. Weka tool Classification Summary

```
x <= 1941
|   y <= 2362
|   |   y <= 2265: YES (3.0)
|   |   y > 2265
|   |   |   z <= 2128: NO (22.0/1.0)
|   |   |   z > 2128: YES (6.0/1.0)
|   y > 2362: NO (640.0/8.0)
x > 1941: YES (632.0/1.0)

Number of Leaves  :     5

Size of the tree :      9
```

```
z <= 2050: YES (10.0)
z > 2050
|   y <= 2373: YES (6.0)
|   y > 2373: NO (22.0/2.0)

Number of Leaves  :     3

Size of the tree :      5
```

Figure 5. Tree Generated by Weka Tool

RESULT

The proposed study comprised of three major phases: first data gathering while using a smartphone accelerometer to get the reading of movement of person the accelerometer dataset consists of three axes, x, y, and z-axis the reading consist of the how many points body is up from the earth, x-axis consists on the vertical position of a body, y consist on the horizontal position of a body, and the z-axis contains the diagonal position of a body. Second, the various preprocessing techniques are implemented on the accelerometer dataset. In this phase, we concise the number of instances by getting the average value of every 52 instances because the dataset consists of 52 instances in one second. So, we got the one instance in one second by preprocessing the dataset, then we separated the classes and balanced the instance of every class. Thirdly, we employed various machine learning algorithms such as Naïve Bays, Random Forest, Multilayer Perceptron, and Decision Tree (J48) classifier for elderly people activities detection and performed comparison of these

method by using various performance metrics i.e. accuracy, sensitivity, specificity, precision, and AUC as depicted in Table 3.

Table 2. Accuracy of Classifiers

Activities	J48	Naïve Bays	MLP	RF
A	98.7	98.05	98.5	98.9
B	92.1	81.5	68.4	84.21
C	98.38	98.38	99.07	99.5
D	83.5	77.91	85.4	84.92
E	94.2	82.6	95.04	95.04
F	96.19	95.23	94.2	95.23
G	89.05	75	83.45	89.59

**The average accuracy of 93.16 is achieved by using Decision Tree J48.

Table 3. Performance Comparison of ML Methods

Classifier	Sensitivity	Specificity	Precision	AUC
J48	97.88	98.8	98.9	99.1
Naïve Bays	94.5	91.25	88.25	87.35
MLP	97.5	96.9	98.35	97.25
RF	87.5	86.5	84.5	85.75

DISCUSSION

To attain maximum accuracy, we performed different preprocessing steps on our dataset and then applied different classifiers on the dataset for better classification performance. There is a total of seven files are locally stored and named from A to G. We stored the number of instances of activity

'A' and stored the equal number of instances of other activities and named as 'YES' for activity 'A' instances and the rest of the instances of activities are termed as 'NO'. In the second file, we store the number of instances of B activity and store the same number of instances of other activity, class of B activity named YES and other to NO. In the third file, we store the number of instances of C activity and store the same number of instances of other activity, class of C activity named YES and other to NO. In the fourth file, we stored the number of instances of D activity and stored the same number of instances of other activity, class of D activity named 'Yes' and other to 'No'. In the fifth file, we stored the number of instances of E activity and stored the same number of instances of other activity, class of E activity named YES and other to NO. In the sixth file, we stored the number of instances of F activity and stored the same number of instances of other activity, class of F activity named YES and other to NO. In the seventh file, we stored the number of instances

of G activity and stored the same number of instances of other activity, class of A activity named YES and other to NO. The accuracy of the different classifiers is illustrated in Figure 6.

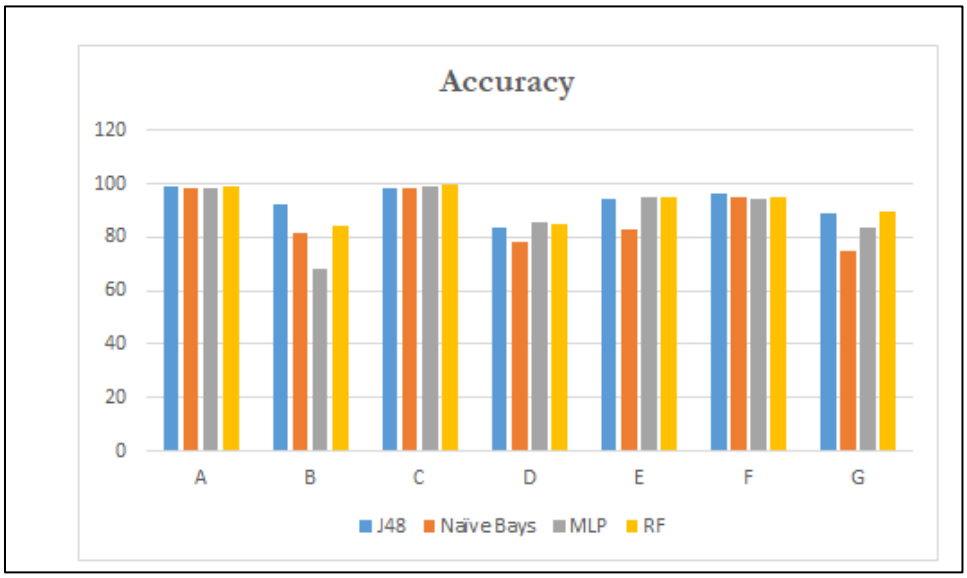


Figure 6. Accuracy graph of various ML methods for elderly people activity detection

Beyond the accuracy measure, machine learning methods are also evaluated using various statistical measures such as sensitivity, specificity, precision, and area under the curve (AUC), respectively. The statistical diagram of these performance evaluation results is illustrated in Figure 7. It can be concluded that the decision tree algorithm (J48) has outperformed the baseline methods for elderly people's activity detection.

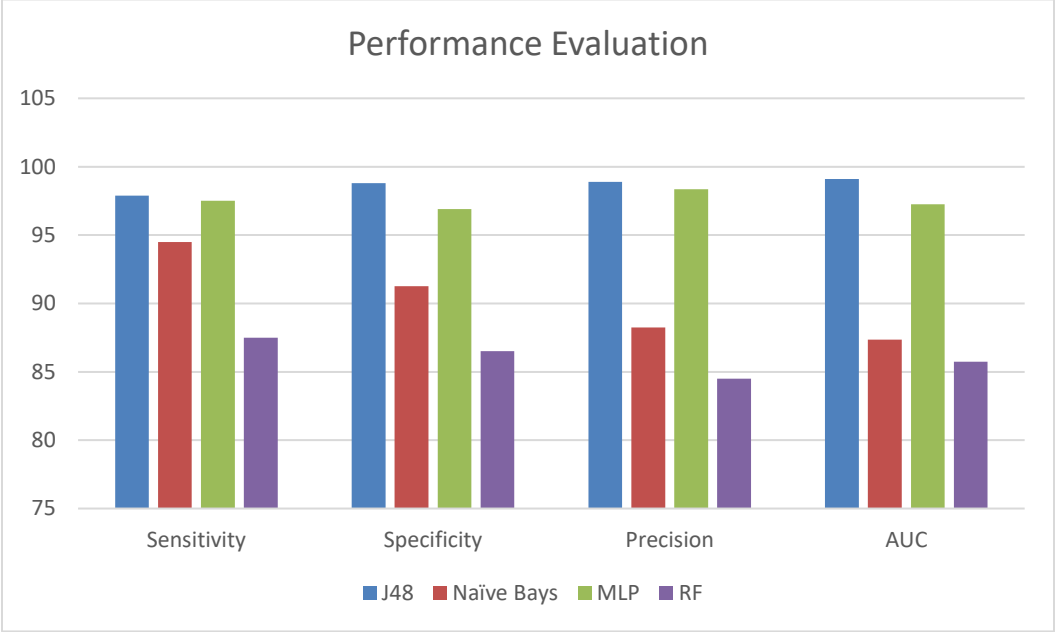


Figure 7. Performance comparison of various ML methods for elderly people activity detection

CONCLUSION

With the advances in technology, sensors embedded in handheld devices have initiated a ground to develop a system for activity detection of elderly people. However, the traditional systems have been affected by the major ingesting of computational resources such as processing units, and memory, etc. Thus, it is required to efficiently detect human activities to provide them aid at the earliest. Moreover, most of the existing human activity detection systems are heavily dependent on the subject's expertise and are expensive. This paper proposes a novel method for activity detection of elderly people using state-of-the-art machine learning methods. The experimental results indicate that the proposed method increases the efficiency of human activity recognition (HAR) and also maintains accuracy. In the future, we intended to implement deep learning algorithms, add more activities, and use various other sensors for activity detection.

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Author's Contribution. M. Imran conceived results. A. Imran wrote the manuscript. A.H. Butt revised the manuscript. A.R. Butt improved the methodology and conclusion section.

Conflict of interest. The authors declare that there is no conflict of interest.

Project details. Nil

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Evaluation of Catastrophic Global Warming due to Coal Combustion, Paradigm of South Asia

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Coal is a carbon containing non-renewable fossil fuel and one of the major contributors of climate change and global warming. We used TANSO FTS instrument in order to obtain the level of atmospheric carbon dioxide through datasets obtained from GOSAT satellite. GIOVANNI was also used to obtain atmospheric concentration of various gases. Burning of coal causes emission of greenhouse gases (GHG) and black carbon (BC) in atmosphere which are responsible for nearly 0.3°C of 1°C rise in temperature. The annual average value of carbon emission for the year 2010 and 2019 is 388.4 ppm and 409 ppm respectively. Since the pre-industrial times CO^2 concentrations have increased up to100 PPM (36%) in the last two and a half centuries (250 years).In South Asia Dhaka has the worst quality of air as CO2 concentration (6.7%) is higher than the country's GDP (5.25%) and energy consumption (4.77%). While an increasing trend GHG has been observed in Lahore up to 5.5 %. This study concludes that the high concentration of carbon dioxide in atmosphere is responsible for average rise of 1.2 °C temperature annually. This temperature rise can lead to adverse climatic conditions i.e., melting of glaciers which will consequently rise the sea level various landmasses may disappear by 2050.

Keywords: Black Carbon, Carbon Dioxide, Global Warming, Coal Consumption

1. Introduction

The atmosphere of earth comprises of various gases which diffuse, attract and reflect different wavelengths. These gases control various atmospheric phenomena including temperature, pressure, humidity and rainfall etc [1]. Black Carbon(BC) and Green House Gases(GHGs) including carbon dioxide, halocarbons, methane and water vapors are responsible for controlling the atmospheric temperature [2]. These gases are responsible for increasing the temperature of atmosphere by absorbing the infrared radiations. GHGs trap heat within the premises of earth's atmosphere [3]. The status of several other components of climate system of earth is altered due to global warming causing the climatic changes. At global scale, the average concentration of carbon dioxide in atmosphere has been increased from 270-370 ppm since the revolution of industries [4]. Burning of coal in industries is major source of BC and CO_2 [5]. The value of CO_2 in atmosphere was too low about 55

million years ago, this concentration increased gradually due to anthropogenic activities [6]. Utilization of coal in human activities and industries has reshaped the environmental conditions [7].

Coal is a combustible fossil fuel used in industries and domestic households for various purposes [8]. It is composed of carbon, Sulphur and small quantities of vicious metals including mercury, arsenic and lead which enter into atmosphere upon combustion [10]. Coal is mostly carbon which reacts with aerial oxygen upon burning giving rise in concentration to carbon dioxide and residue entered in atmosphere as tiny BC particles. BC and CO_2 trap sunlight giving rise to earth's temperature in a process termed as global warming [9]. Coal combustion is responsible for the production of hazardous pollutants that impacts the environment in various ways which include creation of greenhouse effect leading to global warming [11]. Major industrial zones are located in Pakistan, Bangladesh and India. There are significant numbers of chemical intensive industries such as textile, leather, food, fertilizer and pharmaceutical industry in Bangladesh. Pakistan is also a developing country and progressing in several industrial fields; like, fertilizer, mining, leather, chemical, and textile and oil refineries. Pakistan is responsible for 0.9% of total coal consumption of the world. About, 70% of the coal in Pakistan is imported for consumption [12]. One third of the carbon dioxide of Pakistan is emitted through coal fired power plants which is equalant to the amount of CO_2 released through transportation sources i.e., vehicles. Almost, 1.2 million Cars produce similar amount of CO_2 produced by a 1000 megawatt coal fired power plant [13].

Coal mines in eastern South-Asia (India) are also a major cause of air pollution. India's coal production is about 605 million tons, making it the third largest producer globally. India consumes 8% of the total world's coal, making it the third largest consumer of the resource as well. It is also the third largest importer of coal with a total of 160 million tons in imports, trailing behind China and Japan. Around three-quarters (68%) of electricity generation in India depends on coal. The verified coal reserves in India are estimated at 60.6 billion tons as of 2018, ranking again as number three globally[13]. Over 80% of world's energy is obtained from burning of fossil fuels including coal, oil and gas. Among all fossil fuels coal is one of the strong contributors of CO_2 emitter. Nearly 46% of CO_2 is emitted in air by burning of coal. Coal has been the fastest primary energy source in previous decade from the year 2000 to 2020. Mostly the use of coal is in electrical sector. Nearly 70% of the greenhouse gases are emitted from electrical sector due to coal consumption [14].

Global warming is one of the long term environmental impact of coal combustion which is nearly irreversible. Along the increasing temperature, consequences of Global warming include rise of sea level, heat waves, and risks of drought, floods and species loss [15]. If the climatic change due to global warming remained unchecked, it may lead to severe ecological disruption. The main driver of global warming is CO_2 which is released into atmosphere by the combustion of coal in industries [16].

To prevent severe catastrophic environmental conditions, the utilization of fossil fuels must be reduced [17]. The coal combustion is responsible for nearly 0.3°C annual rise in temperature above the level of pre-industrial era [18]. It plays dominant role in changing the climate as a consequence of global warming. To decline the emission of CO_2 in atmosphere, industries must deploy low carbon containing energy resources and make efficient improvements in climatic conditions related to environmental sector [19].

In current scenario, different technologies are emerging globally to capture and store the CO_2 inside the power plant to prevent its loss in environment. These emerging technologies transfer the excess CO_2 in the geological repository. Though this technology can protect the climate however, it is quite expensive, but globally several countries are investing in this technology in order to conserve the environmental conditions of Earth [19].

Combustion of coal produces large quantity of CO_2 which is greenhouse gas that traps heat and in turn causes warming of climate. CO_2 accounts for nearly 72% of total greenhouse gases which are responsible for climatic changes and global warming. Coal is mostly carbon that reacts with oxygen to produce carbon dioxide. Equation 1 shows the combustion reaction of coal in the presence of atmospheric coal.

C + O2 --> CO2. (1)

By burning a gram of carbon nearly four grams of carbon dioxide is produced. On the basis of its type, coal comprises of nearly 60 to 70 percent carbon. Approximately 2 billion tons of coal is being burned annually in power plants around the globe in industrial sector which is responsible for emission of nearly 7 billion tons of carbon dioxide in atmosphere per year. Coal combustion adds nearly 46% of carbon dioxide in Earth's atmosphere. The combustion of coal for the production of electricity contributes nearly 70% of greenhouse gases in atmosphere.

The aim of this study is to estimate the rise in temperature and climatic changes caused by the burning of coal in domestic and industrial sectors. This study aims at analyzing the impact of gases emitted in atmosphere by coal combustion from the years 2002-2020.

2. Materials and Methods

Investigation site

South Asia is a region located at the southern boundary of Asia. The region covers nearly 3.5% of land surface of world. Spatially, it is spread over nearly 5.2 million km^2 area which provide residence to nearly 1.9 billion people [20]. This region consists of eight countries including Pakistan, India, Sri Lanka, Afghanistan, Bhutan, Maldives, Nepal and Bangladesh. From previous few years, temperature of south Asia is increasing gradually.

Figure 1. Study site

Material and methods

Daily product (ACOS_L2_Lite_FP) of atmospheric carbon dioxide prepared at a quality Level 2 (version - 9r) was obtained from TANSO FTS instrument aboard GOSAT satellite. This dataset contains bias corrected Carbon Dioxide column averaged dry air mole fraction. The Greenhouse gases observing satellite (GOSAT) is the first ever satellite designed to measure the two major greenhouse gases i.e. CO_2 and CH_4 from SWIR bands with a temporal resolution of three days.

Concentration of various greenhouse gases was obtained from GIOVANNI. Data acquired from GIOVANNI provided different atmospheric compositions. For the evaluation of natural events, remote sensing satellite data is significant to determine atmospheric compositions at regional and global scales.

Hotspot Identification

In terms of statistics, a region, point or a value that have comparatively higher readings than its surrounding is usually referred to as a hotspot. While in Geostatistics, a geographical dataset in hands spatial clustering or pockets of high and low values are of real importance.

In this particular study, a city is identified as a hotspot only if it has high CO_2 concentration and is surrounded by areas with high values as well. For this purpose, ArcGIS geospatial statistical tool Getis-Ord Gi* was utilized. It helps in identification of the spatial clustering present in a data and performs autocorrelation. Getis-Ord Gi* generates an output feature class with standard deviations (Z scores) and statistical possibilities (P values). A

larger (positive) Z score value indicates a hotspot while a smaller (negative) value indicates a statistically significant cold spot. It can be mathematically expressed as:

$$G_i^*(d) = \frac{\sum_{j=1}^{n} \omega_{ij}\ (d) x_j}{\sum_{j=1}^{n} x_j}$$

Where;
xi and xj represent attribute values of the variable under study in spatial units i and j (years).
d = distance (m)
ωij = weighted matrix

3. Results and discussion

The concentration of carbon dioxide has been increased many folds from the year 2010 to 2019 as shown in the figure 2. Since the advent of industrial sector, at average the concentration of CO_2 in air has been increased from 270 to 350 ppm. Atmospheric analysis through GIOVANNI showed that the concentration has increased up to 2.75 ppm from 2000 reaching up to 4.14 ppm in the year 2020. According to the world meteorological organization (WMO) 2020 has been the hottest year with nearly 1.2 °C rise in temperature above pre industrial era. According to WMO the rise in temperature will reach up to 1.5°C by the year 2024 if the consumption of coal and other fossil fuels remained unchecked. To avoid adverse climatic conditions the average global temperature should not be allowed to rise above 1.5°C. Temperature rise above 1.5°C will cause a significant rise in sea level which may lead to floods, droughts and in turn food insecurity. Figure 2 is presenting the atmospheric concentration of CO_2on box-plot from 2010 to 2019.

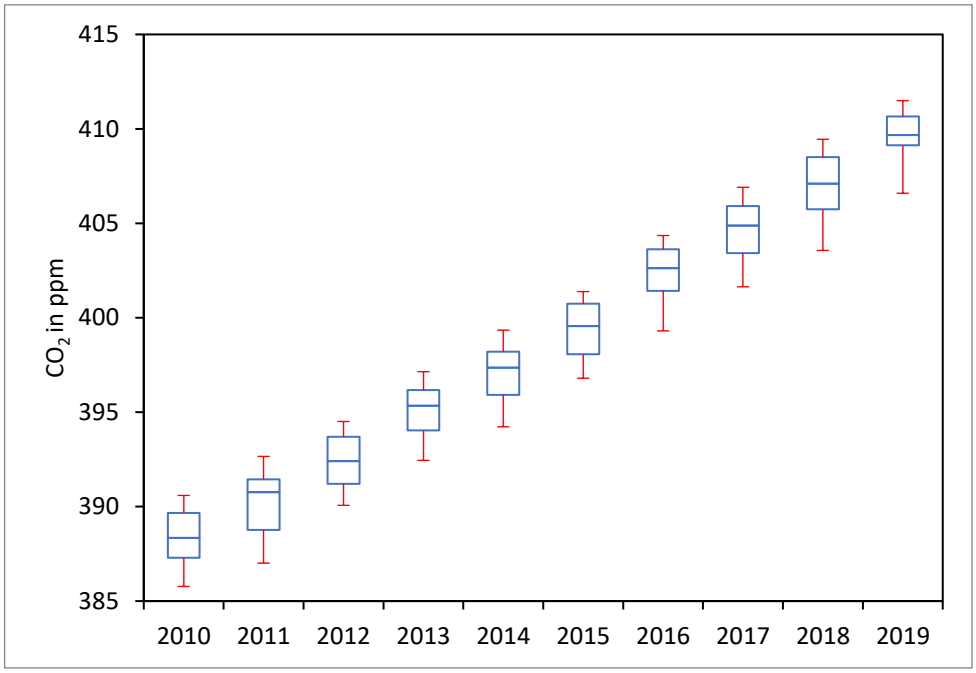

Figure 2. Atmospheric concentration of CO_2on boxplot from 2010 to 2019.

The annual average value for year 2010 and 2019 is 388.4 ppm and 409 ppm respectively that indicates a clear and continuous increase of around 5.3% in the concentration of CO^2 during the last decade.

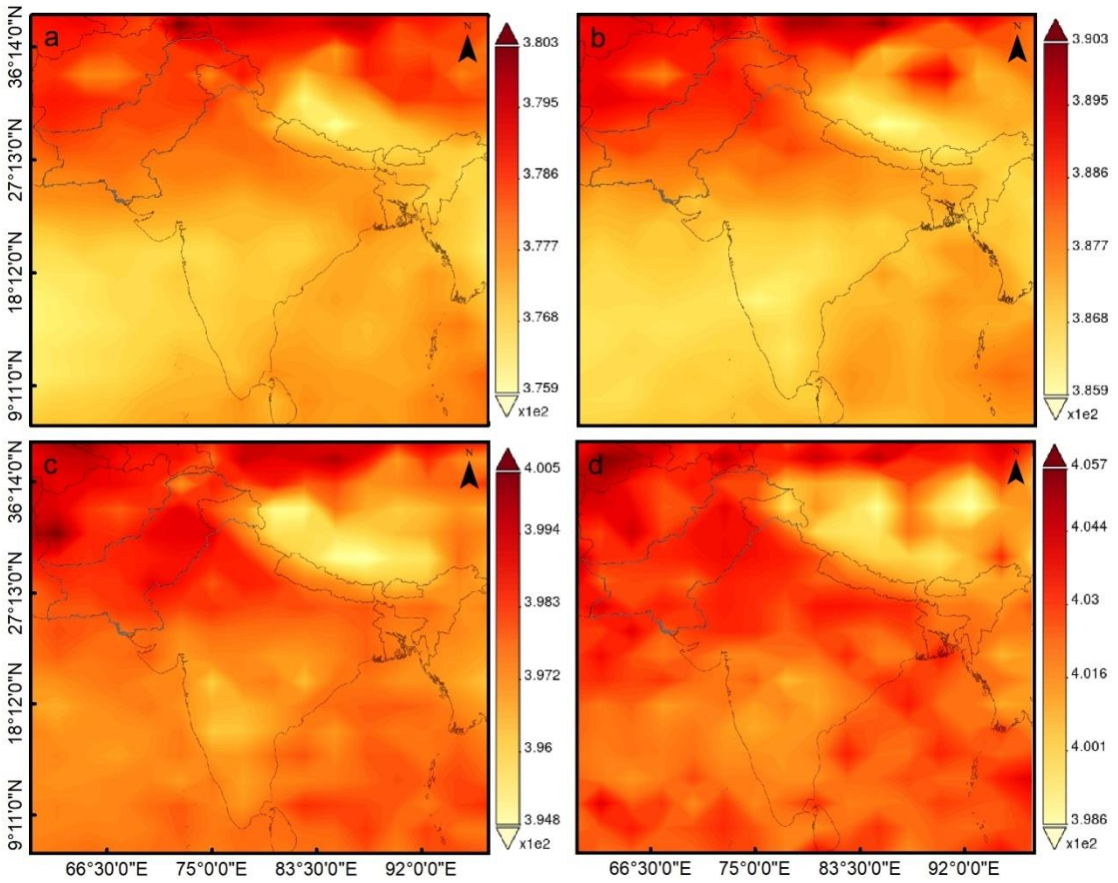

Figure 3. Spatial distribution of CO_2over investigation site during a) 2002-2006, b) 2007-2012, c) 2013-2016, d) 2017-2020. Measured in PPM by AIRS AIRX3C2M v005. Spatial Resolution 2 x 2.5 Deg.

Figure 3 presents the spatial distribution of CO_2over study area from the year 2002-2020 utilizing the AIRS AIRX3C2M v005.In the time span of 2002-2006, the concentration of carbondioxide was highest in North-west region of south Asia which was recorded up to 3.803ppm. In the years 2007-2012 this concentration reached up to 3.903. The level of CO_2 was exponentially increased in the entire study site in the time zones of 2013-2016 and 2018-2020 which was 4.005 and 4.057 respectively in the north-west region.The hotspots were identified by using Getis-Ord Gi* hotspot analysis tool in the study area, as illustrated in Figure 4. These hotspots include some of the major cities of south asia including, Herat and Kabul (Afghanistan), Lahore, Faisalabad and Islamabad (Pakistan), Amritsar, Delhi, Mumbai, Pune and Madurai (India), Dhaka (Bangladesh) and Colombo (Sri Lanka).

The northern part of the South Asia is depicted as a major emitter of CO_2 in the region because of population increase leading towards frequent industrial activities and thus high fossil fuel burning rate. Southern region emits less GHG and is clearer apart from the ports as they are the hub of emissions due to shipping activities. Low emissions can be associated with fewer inhabitants and agricultural activities combined with more humidity

and high air circulations from and to the Arabian Sea and Indian Ocean that aids in diluting the CO_2concentrations.

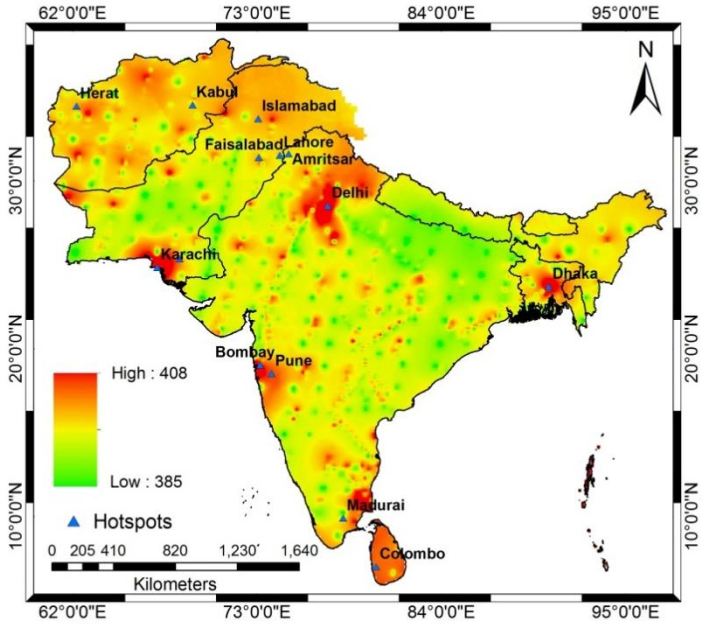

Figure 4. Result of hotspot analysis on point data of GOSAT

Table 1 depicts the average decadal value of CO_2 for each hotspot along with its trend over the years. All the hotspots displayed an increasing trend with Dhaka and Lahore showing the highest increasing trend of 5.5%. Dhaka is known for having one of the worst air qualities in the world and motor vehicles play an important role in polluting its environment by burning petroleum. Some of the previous study proved the results generated in this paper as they revealed the growth of CO2 concentration (6.7%) to be higher than the country's GDP (5.25%) and energy consumption (4.77%). Meanwhile, Lahore showed a high trend of GHG as population is increasing consequently the fossil fuel burning. In addition, the crop burning plays a vital role with the emissions transported from Indian Western Punjab (IWP) pile up the concentration and therefore increase the trend GHG. However, Amritsar depicts the least increasing trend of 4% among all the hotspots. Here, winds play significant role as they scatter the emissions towards the surrounding areas.

Table: 1 Decadal increase in xCO2 concentration over the hotspots from 2010 to 2019

Sr. No.	Hotspots	Coordinates (Lat. N and Long. E)	Area (km^2)	Population (millions)	Average CO2 (ppm)	Trends in CO2 (%)
1	Amritsar	31.6340° N, 74.8723° E	250	1.13	397.3±4.5	4
2	Colombo	6.9271° N, 79.8612° E	37.3	5.6	396.9±4.8	5.4
3	Dhaka	23.8103° N, 90.4125° E	306	8.9	396.3±4.9	5.5

4	Faisalabad	31.4504° N, 73.1350° E	1300	3.2	397.3±4.6	4.9
5	Herat	34.3529° N, 62.2040° E	182	1.78	396.3±4.2	5.2
6	Hyderabad	25.3960° N, 68.3578° E	625	1.7	397.3±4.4	4.7
7	Islamabad	33.6844° N, 73.0479° E	220	1.43	397.4±4.5	4.7
8	Karachi	24.8607° N, 67.0011° E	3780	15	397±4.9	5.2
9	Lahore	31.5204° N, 74.3587° E	1772	12	396.7±4.7	5.5
10	Kabul	34.5553° N, 69.2075° E	275	3.1	397±4.7	5.4
11	Madurai	9.9252° N, 78.1198° E	148	1.47	397±4.5	4.8
12	Mumbai	19.0760° N, 72.8777° E	603	12.4	397.5±4.8	4.9
13	New Delhi	28.6139° N, 77.2090° E	42.7	21.75	398±4.5	4.9
14	Pune	18.5204° N, 73.8567° E	331	3.99	397.2±4.8	5.2

According to studies, since the pre-industrial times CO_2 concentrations have increased to a dangerous level. Various measurements revealed a global increase of 100 PPM (36%) in the last two and a half centuries (250 years). Moreover, studies from Mauna Loa Laboratories in Hawaii depicted a daily mean value as high as 400 PPM in May 2013**.** The only cause of such high and rapid increase in the CO_2 levels over the years is the anthropogenic activities some of which involve fossil fuel combustion, transportation emissions, land-use changes (deforestation), biomass and crop burning and industrial processes[9, 19, 21, 17].

According to NASA once a gas is added in atmosphere it remains in atmosphere for nearly 300 to 1000 years. Anthropogenic activities can significantly cause changes in atmosphere. Half of the concentration of carbon dioxide has been increased after 1980s by the advent of industries. This research revealed that industrial coal combustion has raised the atmospheric temperature up to 412 ppm which is still rising. Since the start of industrial sector nearly 46% of carbon dioxide has been increased when the concentration of carbon dioxide was nearly 280 ppm.

Along the increasing the concentration of greenhouse gases and causing global warming, burning of coal also depletes the level of oxygen in atmosphere as it utilizes aerial oxygen for combustion. In order to control the release of carbon dioxide in atmosphere by burning of coal, carbon capture and storage technologies (CCS) are introduced in several countries of

world. US government has invested nearly 4.8 billion$ in research of CSS in the wake of increasing average temperature of world. This study depicts that the combustion of coal must be reduced globally in order to conserve the natural environmental conditions.

4. Conclusion

Coal is globally being utilized as an energy source. Burning of coal in furnaces and power plants produces carbon dioxide which is a greenhouse gas.Among all hotspots explored in this study Dhaka and Lahore showed the highest increasing trend of carbon dioxide up to 5.5%. The highest trend of CO_2 emission is observed in the north-west region of South-Asia. The concentration of carbon dioxide in atmosphere has been increased from 280-409ppm since the revolution of industries. This high concentration of carbon dioxide in atmosphere is responsible for average rise of 1.2 °C temperature might result inrise the sea level and various landmasses will disappear by 2050. To conserve the environmental conditions the coal consumption must be reduced globally.

Conflict of Interest: Authors declare no conflict of interest while publishing this research paper in IJIST.

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Identifying the Causes and Protective Measures of Road Traffic Accidents (RTAs) in Bahawalpur City, Pakistan

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Road Traffic Accident (RTA) is a growing public issue and fall among the four top causes of mortality and morbidity globally. The main objective of this study was to identify the causes and protective measures of road traffic accidents in Bahawalpur City. Primary data was gathered through a structured questionnaire during a field survey in selected five public places as sample sites i.e. Larry Ada, University Chowk, Bahawal Victoria Hospital (BVH), One Unit Chowk, and Melad Chowk. Secondary data of road accidents was gathered form National Highway and Motor Way Police (NH&MP) while primary data was gathered from 150 respondents (30 from each study site) and analyzed in SPSS software by applying descriptive statistics and road accident risk index (RARI). Findings revealed that the main causes of these accidents include increase in population (62.66%), increase in demand for vehicles (22%), bike drivers (69.33%), overtaking of the vehicles (51.33%), over speed and hustle to reach the destination (34.66%). One wheeling is also a major reason, which results in the death of teenage drivers (52%), violation of the traffic rules (25.33%). RARI results also suggest the relationship between the affected persons and the road traffic accidents. Few suggestions were proposed to overcome the ratio and severity of road traffic accidents because these accidents are predictable and largely preventable through multi-disciplinary coherent strategies.

Keywords: Road Traffic Accidents, Causes, Protection, Bahawalpur, Pakistan.

INTRODUCTION

A road traffic accident is an unfortunate event that normally occur due to carelessness. Ignorance to traffic laws cause collisions between vehicles, pedestrians or any roadside signage and billboards which result causalities. About 30% to 70% of victims have been reported lying on beds in hospitals of developing [1]. Road accidents have become a significant issue concerning the social and economic problems causing disability, deaths and a massive health problems [2,3]. Various studies have revealed that increased costs of living have been observed for disabled persons that usually cost heavily to the poor people [2,3,4]. Road traffic accidents (RTAs) represent a leading and increasing

contributor to regional and global disease burden which have become the 3rd largest contributor to global disease burden by 2020 [5]. Each year nearly 1.3 million people die as a result of road traffic collisions globally, among them more than 3,500 deaths are report everyday on average. Moreover, 20 to 25 million people sustain non-fatal injuries from a collision, and these injuries are an important cause of disability worldwide. Moreover, RTAs are one of the contemporary leading human security threats because it is the global socio-economic crisis [6,7]. Low and middle income countries have suffered from a significant percentage of preventable deaths and injuries from road collisions and under the descriptive analysis, the annual average number of fatal and non-fatal accidents are 43.3% and 56.7% respectively [8,9].

Pakistan is a country having a very dense population and during the previous years, the use of vehicles have been increased exponentially [10,11] that increasd number of vehicles, hence the probability of accidents. A large number of road accidents have been reported in Pakistan, resulting in fatal causalities, deaths and disabilities. Road accidents remain a challenge for policy makers to address the present issue [12]. World Health Organization (WHO) reported more than 25000 road traffic fatalities in Pakistan annually on average. Likewise, WHO estimated the mortality rate per 100 thousand populations in Pakistan that is 14.2 [13]. The economic cost of road crashes and injuries is estimated to be over 100 billion rupees for Pakistan which is estimated to be 2% of Pakistan's GDP [14]. The huge number of injuries and deaths due to road traffic accidents revealed the story crisis of public health and road safety issues.

The main objective of this research is to identify the main causes and possible preventive measures in Bahawalpur City.

MATERIAL AND METHODS

Study Area.

Bahawalpur is a city located in the Punjab province of Pakistan. It is the 11th largest city in Pakistan with an estimated population of 798,509 [15]. It lies between the latitude of 27°-80′ to 29°-50′ north latitudes and between 70°-54′ to 72°-50′ east longitudes. Bahawalpur city is bordered by Yazman tehsil (a sub-administrative unit) to its south and southeast, Bahawalpur Sadder tehsil to its northeast, Lodhran to its north, and Ahmedpur East tehsil to its west.

Data Collection, Sampling and Sample Sites.

In order to collect data about the RTAs, a field survey was conducted in the Bahawalpur city during the months of August September 2019. Primary data was gathered through a structured questionnaire in selected five public places as sample sites i.e. Larry Adda (General Bus Stand), University Chowk, Bahawal Victoria Hospital (BVH) Chowk, One Unit Chowk, and Melad Chowk (Figure 1). Primary data was gathered from 150 respondents (30 from each study site) randomly by filling the questionnaires. The purposive sampling method was used to collect the data and respondents were briefly explained the purpose of the study. The majority of the respondents were male. Different variables including total accidents, fatal and nonfatal accidents, persons killed and injured and a total number of vehicles involved in accidents have been tested statistically. All of these public places have a bunch of people who have been engulfed in the daily road traffic accidents in Bahawalpur City.

Larry Adda is a place which has many congestions of intercity and intracity transport. University Chowk is a center point of the intercity transport. It is situated with the Islamia University old campus gate on the right and Government Sadiq Egerton College on the left. The famous and historical medical center Bahawal Victoria Hospital (BVH), Bahawalpur is also a busy route of daily traffic and also a dangerous point for an accident where traffic signal is also placed. One Unit Chowk is another area where questionnaires were got filled by the people and traffic signals are placed on this road. Melad Chowk is the next busy traffic junction where traffic signals are placed and questionnaires were filled by the people by the customers of nearby commercial plazas and visitors of Gulzar-e-Sadiq park situated on this Chowk.

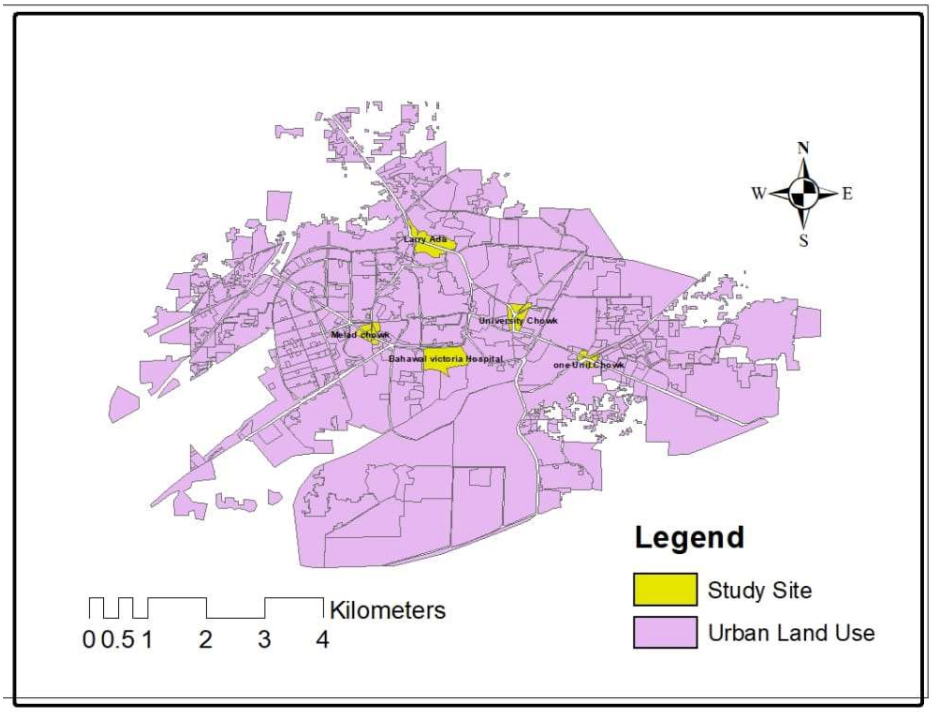

Figure 1: Study area map of Bahawalpur city showing study sites.

Data analysis.

The analysis of the data was carried out by applying descriptive statistics (frequency and percentages) in SPSS 17 software and applied the Road Accident Risk Index (RARI). The obtained data was processed, rearranged, tabulated and presented in tables and graphs to depict the results. Map of RTAs of study sites were prepared in ArcGIS 10.3 software.

Road Accident Risk Index (RARI).

Road safety risk index was applied to the present study and data was gathered from National Highway and Motorway Police (NH&MP). In order to calculate the risk linked with the safety of the roads, a comprehensive index was used to investigate the certain entities of the road safety. The relationship was used to assess the safety of the road [16,17] as shown in the equation (1):

$$Road\ Accident\ Risk\ Index = \frac{Road\ Safety\ Outcome}{Exposure}$$

Following measures were accounted before further proceeding,

(i) the number of the people traveled in kilometers,

(ii) population and number of the registered vehicles.

RARI was calculated by using the minimum number of input vehicles in the study area. Variables for the output were segregated as the number of the accidents (NOA) and number of affected people (NOAP). This risk index was applied to examine the unique value of RTAs risk.

RESULTS

Enforcement of road safety and traffic laws are not deterring the nasty situation on roads in Pakistan. The research for the reduction of RTAs has not been widely executed , than other health issues and is considered as a private or transport sector job, rather than public health issue therefore, the roads in Pakistan are among the dangerous roads in the world [18]. The findings of the study are briefly discussed as below:

Causes of Traffic Increase.

Upon enquiring the reasons of increase in traffic, 5.33% of respondents told that fuel prices were decreased during 2018 which resultantly increased the purchasing power of people and vehicles on the roads were increased due to the low price of fuel. Whereas 10% respondents told that the main factor behind this increase was the reduced prices of vehicles. The greater percentage of about 62.66% responded that traffic has been increased mainly due to increase in population of the country.

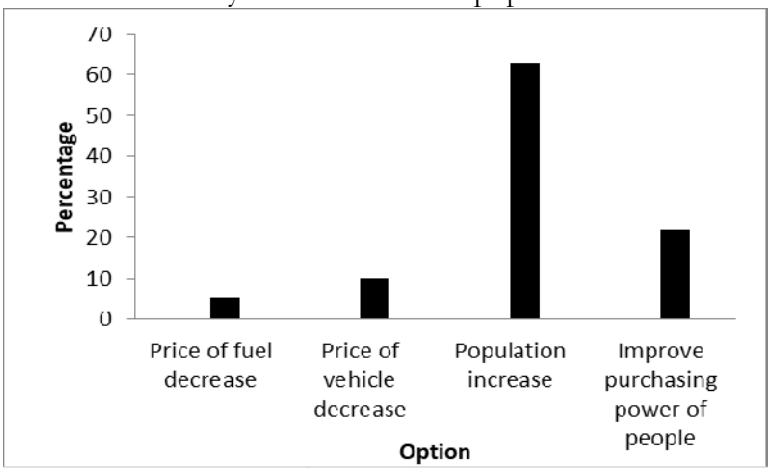

Figure 2: Cause of traffic increase.

Type of Vehicle caused RTA.

About 69.33% of respondents told that bike drivers are the key reason of accidents. Only 2.66% of respondents choose car as a cause of accident because it is four wheeler which can be controlled more easily than any other vehicle. Due to introduction of brands of buses, accidents caused by buses in one way or the other have been reduced drastically as the management does not allow their drivers to over speed the bus, 19.33% respondents replied that rickshaws are also one of the main reason of road accidents, as the drivers are usually illiterate people who do not have sound knowledge of traffic rules.

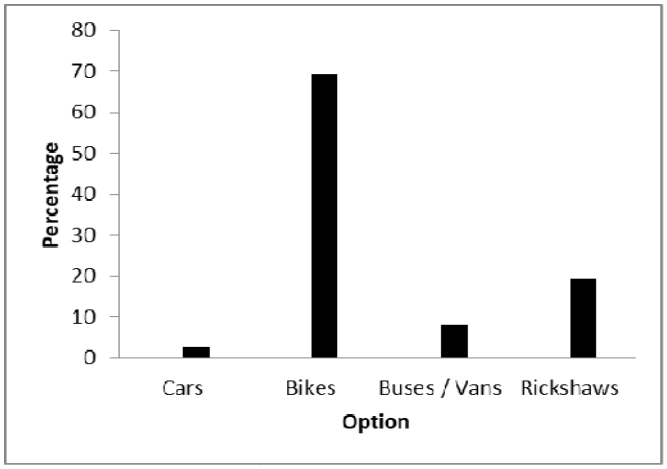

Figure 3: Type of vehicle cause RTAs.

Causes of Accidents in an Urban Area.

About 6% of the respondents replied that bad road conditions, mainly poorly maintained by the management resulting in fatal injuries while 8% of respondents were of view that violation of traffic rules became the leading reason of accidents in urban area. Overtaking cannot be ignored when we discuss about the causes of accidents in urban areas and about 51.33% respondents said that overtaking is the main reason of RTAs because people don't know how and when to overtake. Because of increased vehicles and limited road infrastructure, every person make hustle to reach at destination as responded by 34.66% respondents.

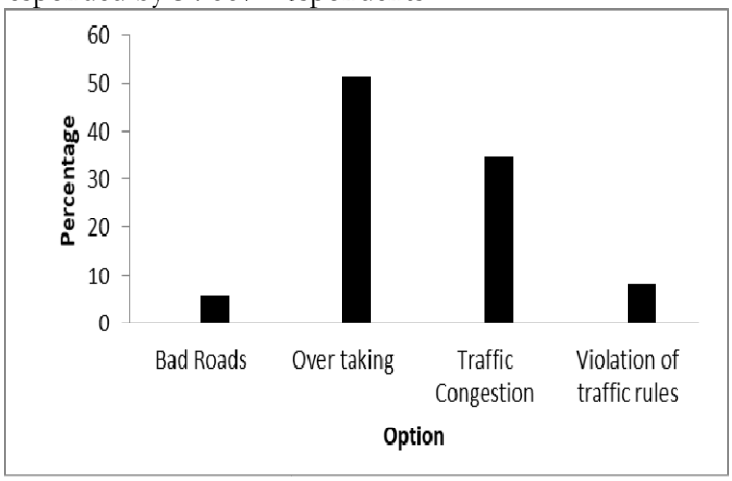

Figure 4: Causes of accidents in an urban area.

Major Cause of Death among Teen Drivers.

About 52% of respondents said that one wheeling is the major reason which results in death of teenagers. While 25.33% respondents replied that violation of traffic rules particularly signals and speed indicators were not followed because of illiterate drivers. Rash driving also hurdles the flow of smooth traffic within the city and 12% of respondents were agreed with this factor. About 10.66% respondents replied that usage of drugs is also one of the main reasons of death when a person drives the vehicle, after using drug that may result in senselessness or unconsciousness due to the medicinal effect which might results in serious nature of accidents.

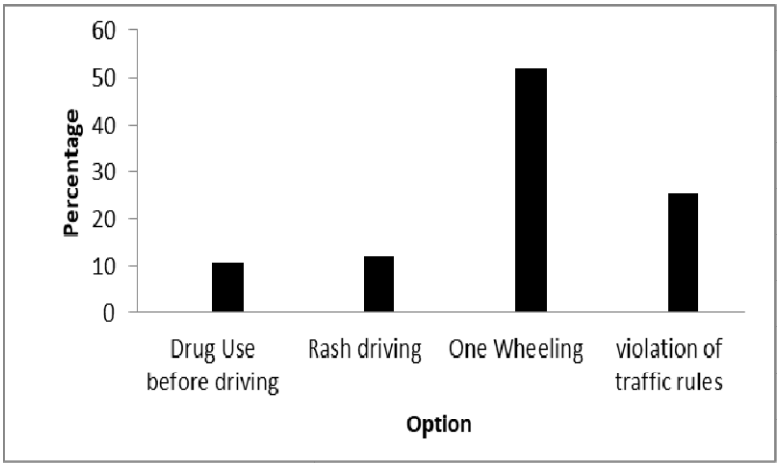

Figure 5: Top cause of death among teen drivers.

Preventing Bike Accident.

Out of total, 12.66% respondents replied that the accidents can be avoided using proper indicators. While glancing from side to side, mirrors play an important role where 11.33% respondents told that use of mirrors are also effective to control the percentage of accidents. Head, brain i.e. the skull part is the most exposed area while riding a bike which can be covered up for safety reasons by using helmet as replied by 20% of respondents. Keeping the speed limit normal, fatal injuries can be reduced as 56% of respondents chosen this option.

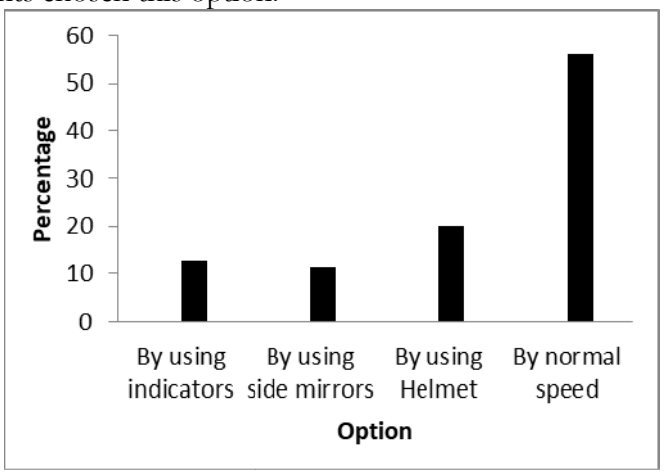

Figure 6: Preventing Bike accident.

Preventive Measures of RTAs.

About 13.33% respondents favored in careful driving to prevent the accident. Use of side mirrors are helpful while crossing the vehicles, that allow the driver to take a full view of their surroundings before making a move and same has been witnessed by 24.66% of respondents. Road sense is most important factor which cannot be neglected in discussing the preventive measures to avoid accidents as 40% respondents were in favor of same option. Often, violation of traffic signals and not stopping at yellow signals results in accident.

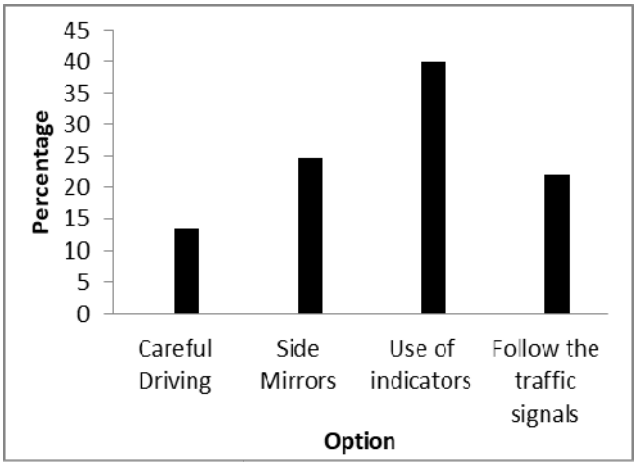

Figure 7: Prevention from RTAs.

DISCUSSION

It is evidence that the economic conditions of Pakistan were much better in 2017 and 2018 where purchasing power of people was increased, which maximized the demand of vehicles as responded by 22% of respondents. Meanwhile, speeding during a night condition also results into fatal traffic accidents. Careless human behavior contributed about 95% to road accidents. Similarly, in regard to the above data compilation more emphasis should be placed on human factors related to driving behavior [20]. The common causes of road accidents are bad eyesight, long reaction time, over-speeding, overtaking, neglecting of vehicle maintenance, incorrect application of driving aids, driver's mental and physical fitness, use of alcohol, use of drugs, fatigue, lack of education, training, age, religious influence, vehicle ownership, and use of charms as protection by drivers [21]. In a survey-based analysis held in Islamabad, the capital of Pakistan, the data taken from the hospital showed that 87% RTA cases occur due to the negligence of traffic laws [22]. Moreover, Availability of low cost vehicle, bike is usually used for travelling purpose, generally within the city. Therefore, the numbers of bikes have increased exponentially which augmented the road traffic. In Pakistan, the pedestrians and the rider of motorized (2 or 3 wheelers) are at a greater risk and the leading cause of RTAs fatalities are 41% and 39% respectively [23]. Poorly constructed road curves and relevant infrastructures would result in an extremely high accident rate and severe accident severities on curves [24]. Vehicle and equipment designs are also very important as a strategy for reduction of the burden of RTAs. Therefore, the design of locally manufactured vehicles needs to be improved in order to make them safer on the roads [25]. A study conducted in Karachi (2007-2014) showed that the highest number of fatalities were borne by riders of two-wheelers (cyclists and motorcyclists) which is 37.2% followed by pedestrians (35.80%) showing extreme pedestrians' vulnerability to RTAs in urban environment [29]. Additionally, the traffic law enforcement has shown poor performance and there is non-compliance to seat belt usage and helmet wearing in Pakistan [25,30].

RTAs are growing public issue and fall among four top causes of mortality and morbidity of different age groups. Flow of traffic nowadays has been increased therefore drivers should remain more careful about the uncertain happening. Therefore, the RTAs are predictable and largely preventable through multi-disciplinary coherent preventive strategies [31].

Results of the Road Accident Risk Index (RARI).

The Road Accident Risk Index (RARI) was applied where the data of 88 cases of road traffic accidents were analyzed. Table 1 depicts the volume/ capacity (V/C) of vehicles and vehicles hours of travelled (VHT) as input variables and number of accidents (NOA) and Number of affected persons (NOAP) as output variables and tested for correlation analysis. In order to establish the statistical relationship between the factors of the traffic flow and severity of the road accidents and vehicles, and was designated as safety output. The results suggest that after applying model for calculating risk in accident data analysis and management field, the lowest level must be measured as the measure of road safety. Therefore, this model has been applied to analyze the concept for road safety analysis too.

Table 1. Description of the road accidents data index analysis.

Stage	Variables	Description	N	Mean	SD	Min	Q1	Med.	Q3	Max
Output	NOA	No. of accidents	88	-	-	1	1	1	2	12
	NOAP	No of affected persons Killed or injured	88	-	-	1	3	4	6	158
Input	V/C	Volume / capacity	88	0.40	0.006	0.001	00.40	0.52	0.58	0.56
	VHT	Vehicles Hours Travelled	88	7280	3536	3234	3635	3237	3638	3739

Note: N is the number of the road accidents
SD: Standard Deviation Q1 and Q3 quartiles of the data, NOA Number of accidents, NOAP number of affected, injured or killed persons

CONCLUSION

Road traffic accident (RTA) is a critical public health problem and is a growing public issue and fall among four top causes of mortality and morbidity of different age groups. The findings of the study revealed that the increase in population boost the demand of vehicles which also increased the road traffic accidents especially the bike accidents, followed by the rickshaws. Therefore, based on the findings, it is summarized and recommended that awareness should be provided to the common masses towards the improvement in road safety. For this purpose, City Metropolitan Corporation can make a long term policy for the infrastructure of the roads conditions, repairing and timely maintenance of roads in the city with special focus on the most busy and excessively used roads.

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Author's Contribution. Muhammad Atif Nazeer: Carried out the field survey and data collection, M Mohsin: supervised the research and did preliminary review. Abdul Rehman: Performed in data analysis and write-up of the manuscript.

Project details. This research is part of the BS Geography research project carried out by the first author and supervised the second author.

Conflict of interest. Authors declares no conflict of interest for publishing this manuscript in IJIST.

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Estimation of Relation Between Moisture Content of Soil and Reflectivity Index using GPS Signals

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Abstract

The irrigation system throughout the world is affected by the variations in water content due to different soil structure, textures and climate change. The irrigation system supplies sufficient water to the agricultural fields in order to fulfill the prerequisites. The measurement of soil moisture content (62%) is crucial for precision irrigation and sustainable agricultural system. Site specific agricultural system was utilized to overcome all issues related to soil water moisture contents in the paddock. Smart technology was utilized to record GPS signals through the sensors developed by National Aeronautics and Space Administration (NASA) utilizing the signals reflected on the Earth's surface. The GPS system was utilized to analyze dielectric soil properties and moisture content in proposed areas. The main objective of this study was to determine water content with stimulus soil type, ground cover and compaction on the irrigation system by utilizing the GPS-based techniques. The result indicated positive relation between soil moisture content and the signals reflected on the earth surface. All factors affecting the irrigation system were not related to the reflected signals and did not affect the soil moisture content. The reflectivity was not reduced by ground cover. Whereas, comparative relationship was found between soil moisture content and reflectivity index i.e. soil moisture contents were increased with reflectivity index up to 0.02 %. The results showed that GPS signals system have significant impact on estimation of soil moisture content in precise irrigation system.

Keywords

Remote Sensing, Soil Moisture, Reflectivity index, GPS, Site-Specific Irrigation

1. Introduction: Agricultural management requires up to need water supplies which is now being analyzed using a new concept which is Site-specific or Variable-Rate Irrigation (VRI). This technology is significantly used to reduce water utilization, nutrient leaching and runoff [1]. Soil retains a definable amount of water which is commonly known as moisture content of soil. A successful site specific irrigation system is obtained through continuous measurement of moisture content of soil [2]. Behavior of soil is significantly affected by the moisture content, therefore it is essential to accurately monitor the moisture content of soil.

Water content of soil significantly affects the nutrients and content of moisture and influence the aeration of soil. Moisture content of soil keep changing the availability of water through irrigation or rainfall. Availability of moisture in soil is highly significant for effective growth and efficient functioning of plants. Lack of adequate water content in soil lowers the crop yield which can lead to root proliferation, reduce growth and stomatal conductance, impair pigments and reduce protein content in plant [3].

In this modern era, the moisture content of soil can be measured through smart technologies. Volumetric and percentage water content of soil can be analyzed using modern techniques. It can be measured using different kind of sensors including TDR, multi-sensor capacitance probes and tensiometers [4]. A significant number of sensors are required to provide sufficient data regarding spatial variability of irrigated fields since the sensors in a production field measure the moisture content of soil at distinct locations [5,6]. Thus utilizing sensors for determining moisture content for site specific irrigation system can be impractical and expensive [7,8]. Therefore, advanced remote sensing techniques are required for these kinds of measurements [9, 10].

The varying dielectric properties of soil are sensitive to frequency ranging from 1 – 2 GHz and this frequency can effectively penetrate through the vegetation [11, 12]. The dielectric properties of soil are closely related to the moisture content of surface of soil. Civilian-use carrier signal i.e, L-band at a frequency of 1.575 GHz is utilized for measuring moisture content through remote sensing technology [13].

GPS is satellite based global positioning system which is based on the continuous transmission of information in coded form. Initially the GPS system was only for military use but later on it was intended for civilians because of its wide range of applications [14]. The main objective of this study was to determine water content and influence soil type, ground cover and compaction on the irrigation system utilizing the GPS-based techniques. The GPS effectively analyzes the dielectric properties of soil. In addition to the general functions of positioning and navigation, the GPS can also be utilized for various other functions including remote sensing, sensing of atmosphere and monitoring of earthquake and surface deformation [16].

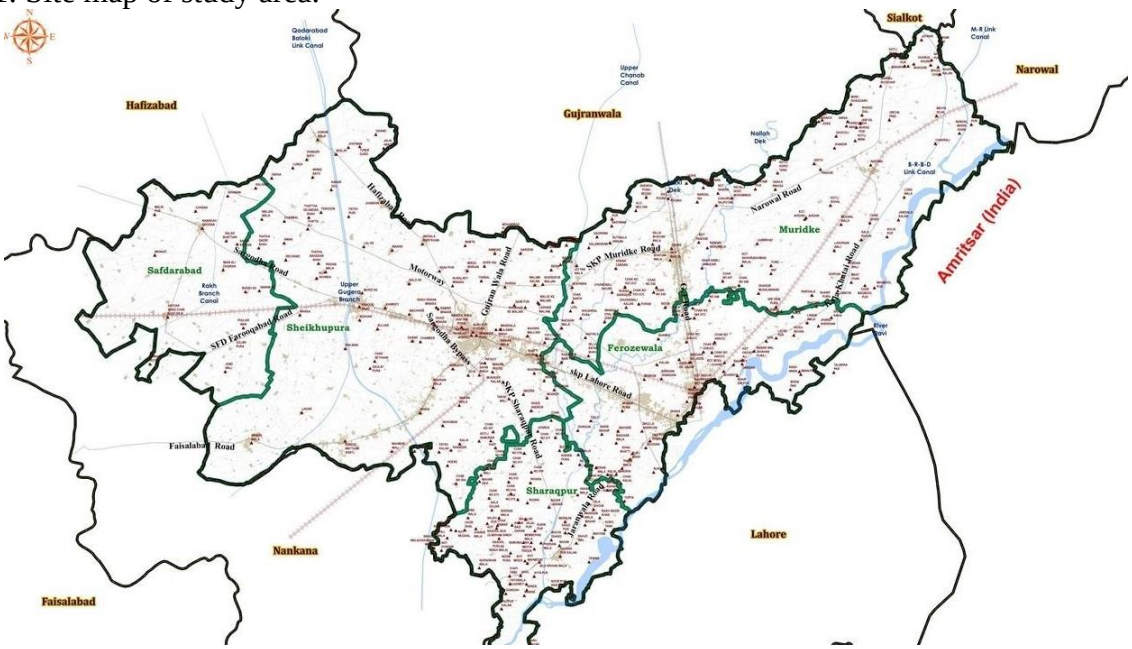
The signals are reflected and directed by the object, which are received by GPS receiver antenna. GPS receiver antenna is highly sensitive to the moisture content. This system works by recording the signal to noise ratio (SNR) [16]. The signals are varied as the moisture content of soil near receiver antenna changes. Thousands of geodetic quality GPS receivers are being utilized throughout the world. Geodetic quality receivers are highly efficient and cost effective method accurately determines various geophysical parameters including moisture content of soil [16].

The geodetic quality GPS antenna collects both reflected and direct signals, which are further processed by the receiver. This study aims at utilizing GPS signal strength for the estimation of moisture content of soil through determining Signal to Noise ratio (SNR).Multiple regression models are utilized in this paper for determining the relationship between reflectivity index and moisture content of soil.

Study Area

This study was conducted in Sheikhupura which is a district of province Punjab. By population it is the 16th largest city of Pakistan located at 38 km at northern side of Lahore. This district covers nearly 75 km² of area. The district resides nearly 230km above the sea level. The climate of this district ranges from maximum ranges of 45 **ºC** in winters to minimum 1 **ºC** in winters. The annual rainfall in this region ranges up to 500mm. the slope doesn't affect the distribution of water as the study site is a plain area. The study area is mapped in figure 1.

Figure 1: Site map of study area.



Methodology

Three different types of soils were selected to conduct tests repeatedly these soil types include Fuquay sandy loam, Lakeland sand and Faceville loamy sand. The study area was a 2.5 ha field located in sheikhupura [17]. Commercially available Electrical conductivity (EC) was used to obtain electrical conductivity of soil which in turn was used to determine the varying dielectric properties of soil. The electrical conductivity of 0.3 to 0.9 m of top soil was measured by using veris-3100 which is similar to small disk harrow which has a width of 2m [18]. Nearly 20 measurements were taken for a 15 m long plot at the rate of 1 Hz. SS tool box was used to develop a thematic map of electrical conductivity [19].

The faceville soil consists of higher EC and clay content were compared with the Lakeland soil. The average values of electrical conductivity were observed of Fuquay, Faceville and Lakeland are 9.2, 12.9 and 4 respectively. Depending upon the electrical conductivity of

soil, the test field was divided into three zones and 21 plots. All plots were supplied nearly 2.5 cm of water and the reflected signals of GPS were collected for all plots. The average value of moisture content was recorded within three days is 8.0%, 6.8%, and 2.9%, respectively. There was no rain within the experimental days [20]. Different soil compactions are created using tractor over plots. The compactions were created within a day and followed by 2.5 cm irrigation. GPS based hydraulic penetrometer was used to collect solid data. The resistance to penetration was quantified using geo referenced data. The values of soil compaction values were obtained by measuring force and average value of CI was 3.2 MPa.

A DMR from 9-m tower was used to take measurements of ground reflectance from the center of rectangles. The equation 1 given below, was used to calculate resolution. where "A" represents footprint of the reflected signal (m^2), "h" shows height of receiver above the surface (m), "λ" shows the incoming signal wavelength equal to 19.03 cm, and γ is the elevation angle of satellite signal.

$$A = \pi * \frac{\sqrt{h\lambda \sin\gamma}}{(\sin\gamma)^2} * \frac{\sqrt{h\lambda \sin\gamma}}{\sin\gamma} \qquad (1)$$

By changing the angle and height of antennas, the resolution of DMR also changes. The receiver of the software accepts high elevation to make a specific area of reflection just below receiver. The angle of elevation changes from 60 to 90 degree at the height of 9 m. The reliever of GPS located in each plot in such a way that reflected signals cross the middle portion of plots. The predicted paths were mapped corresponding to the plots. Figure 2 illustrates the top and bottom sides of DMR which are measured using RF power divider.

Measurements of moisture content for soil were taken from each plot using a soil probe of almost 5 cm. The direct and reflected signals were collected over time using a DMR receiver on exact locations in each plot. Each core of soil was divided into 5cm thick layers and the content of moisture is determined. The soil sample was taken from each layer and the sample is then labeled, weighed and dried at 105˚C for 24-hours through standard procedure.

The satellite tracking antenna was used to determine the reflectivity by developing a ratio of reflected power and power determined. The data of reflectivity was utilized to obtain soil moisture data by developing simple linear regression model. The slope parameter and coefficient of determination (R^2) of simple linear regression model was determined using analysis of variance F-Tests. Along the determination of soil moisture the linear regression model also calculated for soil type, soil compaction and crop biomass.

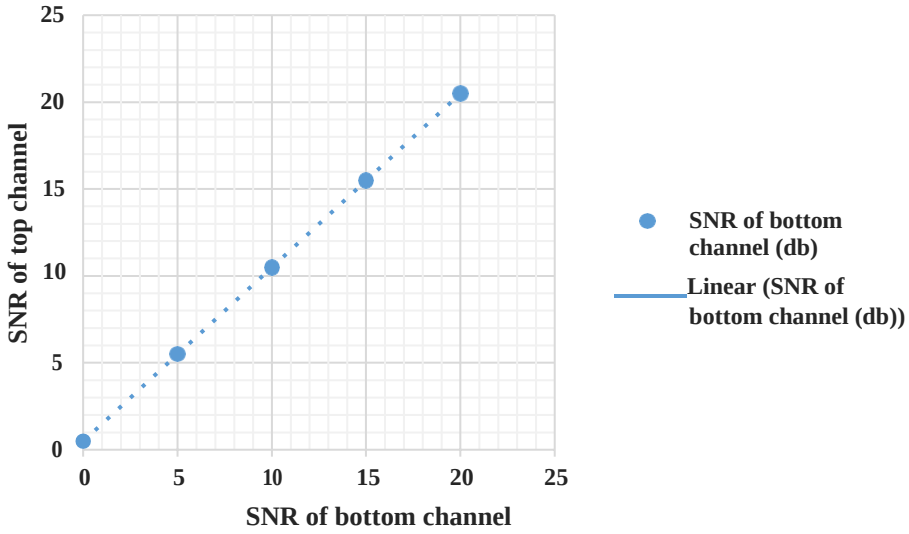


Figure 2. RF power divider was used to measure SNR of top and bottom channels of DMR Significance of parameters are determined using ANOVA F-Tests. The JMP 10.0.0 and tests were utilized to calculate a significance level of 0.05.

Results and discussion

The reflected index of top 25cm layer of soil was determined 0.788. Moisture content of soil changed from 1 to 12% during the measurement of reflectivity. The linear model of reflectivity index is:

$$RI = 0.1389 + 0.0273\boldsymbol{M} \qquad (2)$$

In the above stated relationship, M indicates the moisture content. The increase in reflectivity per moisture content was estimated to be 0.0269. This result showed that the linear regression model can estimate moisture content of soil from reflectivity.

Figure 3 showed the relationship between the reflectivity index and soil moisture contents separated by treatments (COM, CROP, NC). The slopes of regression lines were determined using multiple regression model.

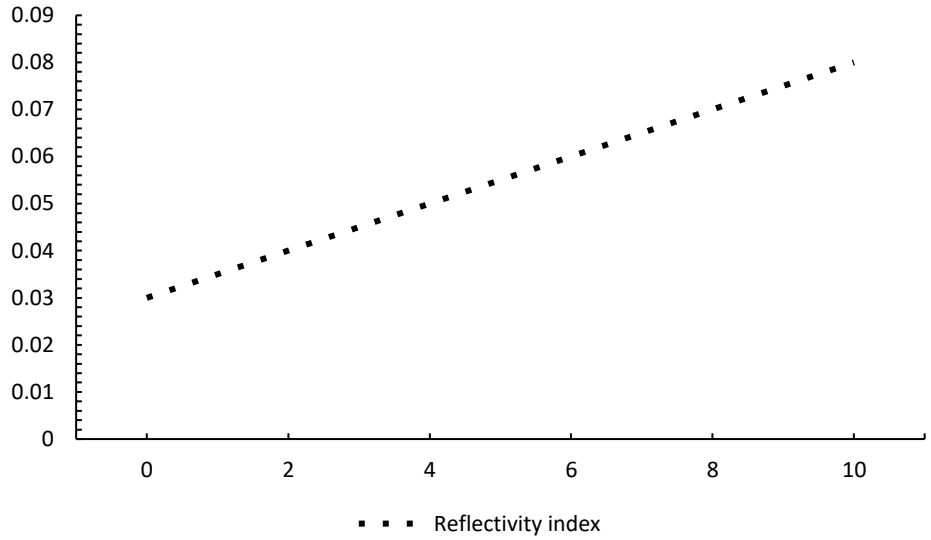


Figure 3. Effects of soil moisture contents on reflectivity index.

Regression line slopes were 0.03, 0.02, and 0.02 for NC, COM, and CROP, respectively. Figure 3 shows the relationship between the reflectivity index and soil moisture contents separated by the three treatments, soil types (Lakeland, Fuquay, and Faceville). Positive relationship between moisture content and reflectivity index was shown by each treatment.

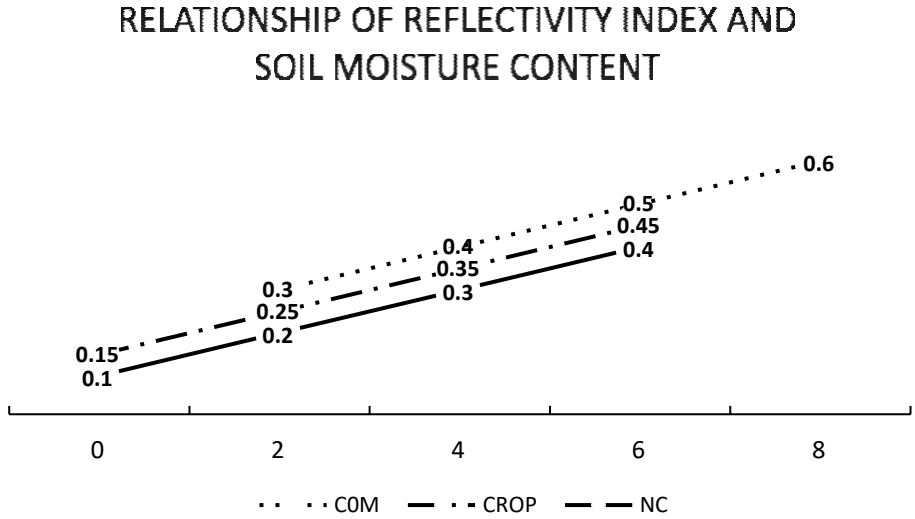


Figure 4. Relationship of reflectivity index and soil moisture contents separated by-treatments: compacted (COM), no compaction (NC), and ground cover (CROP).

Table 1. ANOVA results of reflectivity index versus moisture and treatment.

Source	DF	Sum of Squares	Mean Square	F Ratio
Moisture	1	0.37613275	0.3713275	131.0980

Source	DF	Sum of Squares	Mean Square	F Ratio
Treatment (COM, NC, CROP)	2	0.04995747	0.0249787	8.7061
Treatment by Moisture	2	0.00615571	0.0030779	1.0728
Total	76	0.68676087		

Table 2. ANOVA table of reflectivity index versus moisture and soil type.

Source	DF	Sum of Squares	Mean Square	F Ratio
Moisture	1	0.30355215	0.30355215	82.8923
Soil Type	2	0.01271813	0.006359	1.7365
Soil Type by Moisture	2	0.00429694	0.0021484	0.5867
Total	78	0.77412139		

Table 3. ANOVA table of reflectivity index versus moisture and actual compaction measure.

Source	DF	Sum of Squares	Mean Square	F Ratio
Moisture	1	0.40542071	0.40542071	131.4979
Compaction	1	0.00093599	0.00093599	0.3036
Compaction by Moisture	1	0.00865725	0.00865725	2.8080
Total	52	0.58067948		

Table 4. ANOVA table of reflectivity index versus moisture and actual crop biomass measure.

Source	DF	Sum of Squares	Mean Square	F Ratio
Moisture	1	0.56627584	0.56627584	157.4121
Biomass	1	0.00571571	0.00571571	1.5888
Biomass by Moisture	1	0.00058714	0.00058714	0.1632
Total	78	0.84252875		

The relationship of moisture and reflectivity were found consistent according to the results, two multiple regression models were developed to analyze the relationship. One of these models illustrate the soil compaction and moisture while the other model shows the measure of crop biomass. Table 3 and Table 4 presented the ANOVA F-test results for these models. The regression lines were not different for different biomass and compaction measure.

The analyses showed that changing the depth of sample the sensitivity of L-Band towards the soil moisture content is also changed. The figure 5 shows relation of R^2 and sampling depth.

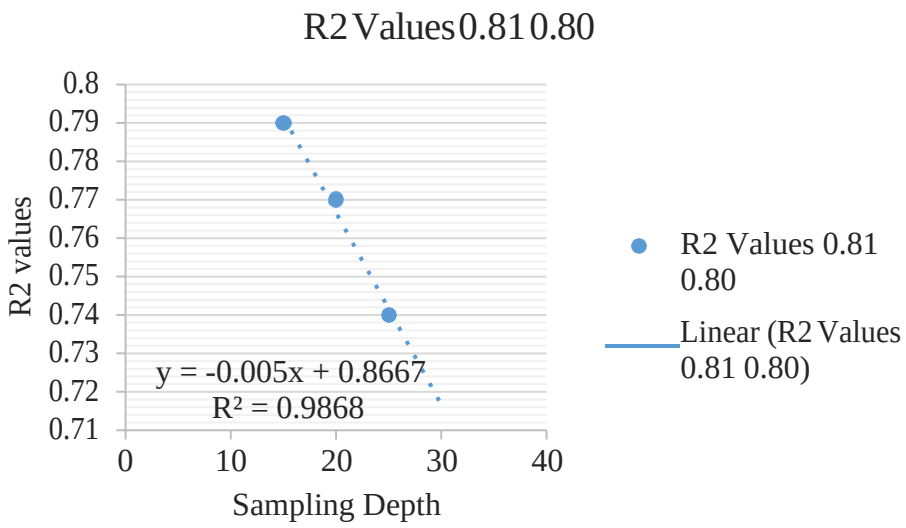


Figure 5. Relationship of R^2 and sampling depth.

The R^2 value is for the coefficient of determination of the reflectivity index and moisture linear relationship at a particular depth. The strongest relation of moisture content and reflectivity index was observed in first 5 cm of soil sample. The value of R^2 decreases as the depth of soil increases. This decrease in value is due to less penetration of GPS signals into the soil.

A positive relation between moisture content of soil and signals reflected by soil on the earth surface is observed. The GPS signals neither affect the moisture content of soil nor changes the irrigation system. While the reflectivity index is affected by the depth of soil. The ground cover did not reduce the reflectivity. While, a comparative relationship was found between soil moisture content and reflectivity index i.e. soil moisture contents were increased with reflectivity index up to 0.02 %.

Conclusion

A comparative relationship was found between moisture content and reflectivity index, when the soil moisture is increased the reflectivity index is also increased up to 0.02 %. The results showed that technology plays a significant role in estimating moisture content of soil in the management of site specific irrigation.

Conflicts of Interest

The authors declare no conflicts of interest.

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