Leveraging Generative AI to Learn Impact of Climate Change on Buildings on Urban Areas

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Climate change, global warming, and pollution are intensifying daily. As urbanization increases, understanding the reciprocal impact between buildings and the environment becomes increasingly important. While most research on building monitoring through the Internet of Things (IoT) emphasizes energy consumption and data collection, it often overlooks the effects of outdoor environmental factors on buildings and vice versa. Additionally, existing studies frequently lack detailed reports that clarify their findings. This work aims to expand our understanding of environmental influences on buildings, indoor environments, and residents. It also seeks to generate comprehensive reports on these impacts, providing actionable recommendations to mitigate and minimize them through the use of Generative Artificial Intelligence. Specifically, we fine-tuned Large Language Models (LLMs) such as Generative Pre-trained Transformer 2 (GPT-2) and Large Language Model Meta AI 2 (LLAMA2-7b), using the Nous Research LLAMA2-7b-hf version from Hugging Face, on a custom dataset compiled from diverse online sources. Our research examines the effects of environmental factors, including temperature, humidity, and air quality, on urban buildings and indoor environments, with these models generating reports that offer practical recommendations. The generated reports offer a clear understanding of environmental impacts on buildings and suggest strategies to minimize these effects. These insights are intended to support effective urban planning and sustainable development. By implementing these recommendations or best practices, we can enhance indoor environmental quality while reducing contributions to global warming. Future work will involve continuous monitoring of buildings' indoor environments, energy consumption, and greenhouse gas (GHG) emissions, further reducing GHG emissions and addressing global warming.

Keywords: Generative AI, Buildings, Climate Change, Environment, Global Warming, Large Language Models, Transformers.

Introduction:

The impact of climate change on buildings, and vice versa, is becoming a critical challenge as urbanization accelerates alongside population growth, which drives demand for more buildings and homes. Currently, cities are constructing large buildings that consume substantial energy and emit significant amounts of heat and carbon dioxide [1]. Within nearly every building, from large complexes to small structures, numerous machines and appliances require energy and produce heat [2], ultimately affecting the environment. The world is already grappling with climate change issues such as global warming, which is considered one of the most serious global challenges. According to the National Centers for Environmental Information (NCEI) [3], the global average temperature has risen by approximately 2°F (1°C) since the pre-industrial era (1850-1900). Although this change may appear modest, it represents a substantial increase in accumulated heat.

Research on building monitoring has included areas like energy consumption and heat management [4]. For example, green roofs have been studied for their ability to reduce air conditioning needs, mitigate noise, and decrease energy demand through passive components [5]. Moreover, IoT technology has enabled monitoring of indoor environmental conditions [6], although it often lacks documentation of the observed impacts. It is essential to conduct a two-way analysis of the environmental effects on buildings—both in terms of the changing climate's impact on buildings and their indoor environments, and how buildings themselves affect the outdoor environment. In this context, Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) are advancing to help reduce and manage climate change effects [4]. Today, Generative AI, specifically Large Language Models (LLMs), can be applied to generate content on causes, impacts, and more [7][8][9].

For this research, we conducted an extensive analysis to understand the impact of outdoor environmental factors on buildings and their indoor conditions. Our focus centered on three parameters: temperature, humidity, and air quality index. We reviewed articles, research papers, and specialized sources, and analyzed historical and current environmental data from the region to compare parameters such as temperature. By examining these variables, we identified environmental impacts on buildings. Using Large Language Models, we generated detailed reports and recommendations to help us understand the specific environmental effects related to temperature, humidity, and air quality, and to determine best practices for mitigating these impacts.

The Large Language Models (LLMs) [10][9][8] used for this study have demonstrated considerable potential in generating human-like text. However, many open-source models face challenges in executing domain-specific tasks and accurately following instructions [8]. To improve precision and relevance for our specific research requirements, we fine-tuned LLMs, including GPT-2 [9] and LLAMA2-7B [8], for domain-specific text generation. This customization enhances the model's ability to produce more precise and contextually appropriate content for our research objectives.

This study proposes using Large Language Models to generate impact reports based on outdoor parameters, such as temperature, humidity, and air quality index, to assess their effects on indoor building environments and occupants. The goal is to thoroughly understand these impacts and offer mitigation strategies that minimally affect the outdoor environment. Generative AI facilitates the creation of comprehensive documents that effectively describe these impacts. Our primary focus is on analyzing environmental factors' impact on buildings and providing detailed reports with recommendations through LLM-generated reports. Future objectives include ongoing monitoring of indoor building environments.

Objectives:

The primary objectives and contributions of this research are as follows:

- Gaining a comprehensive understanding of how environmental conditions interact with buildings and their indoor environments.
- Leveraging the capabilities of Large Language Models to generate detailed, context-specific reports on the impacts of outdoor environmental factors on buildings.
- Fine-tuning advanced models, such as GPT-2 and LLAMA2-7B, to develop an automated system that can interpret and synthesize complex environmental data into actionable insights.
- Producing and delivering these reports to support improved urban planning, design, maintenance, and sustainability.

Novelty:

The novelty of this study lies in its use of Generative AI—specifically through the fine-tuning of Large Language Models, including GPT-2 and LLAMA2-7b—to analyze the effects of environmental factors such as temperature, humidity, and air quality on urban buildings and indoor environments. By generating reports that include actionable recommendations for mitigating these effects with minimal impact on the outdoor environment, this approach offers fresh insights into sustainable urban planning and climate impact mitigation.

The remainder of the research paper is organized as follows: Section 2 provides a literature review, discussing related works and their contributions. Section 3 details the proposed research methodology, including data collection, organization, analysis, and the complete flow for model training. Section 4 presents the experiments conducted and the results of the proposed research work. Finally, Section 5 concludes the study by summarizing its motivation, contributions, suggested improvements, and the future work planned to extend this research.

Literature Review:

Various research studies have focused on building monitoring in key areas such as structural health monitoring (SHM), load monitoring, energy consumption, and building automation. For instance, in [1], researchers compared the environmental performance of large wooden buildings, considering thermal inertia and key drivers of environmental impact. This study also demonstrates that building materials can amplify or mitigate environmental effects. Additionally, [4] explores the use of machine learning and AI techniques to enhance building efficiency and reduce environmental impact.

Green roof systems are another approach gaining attention for mitigating environmental impacts amidst increasing urbanization and energy demand. In [5], the authors proposed passive systems, specifically green roofs, which can reduce air conditioning needs in hot weather and provide positive effects on outdoor environments. Their study, conducted on Sicilian buildings in Italy, addresses gaps in energy and environmental assessments. However, challenges such as ongoing maintenance, high construction costs, and potential roof leakage pose significant barriers.

Building monitoring systems often include IoT devices for tracking indoor environmental factors like humidity, heat, and moisture. In [6], an ESP Duino system was proposed to collect data on indoor environment metrics such as humidity, temperature, and CO2 levels. This system includes server and data collection layers with multiple modules but focuses solely on data collection and preprocessing, without leveraging the data for insights or predictive analytics. Large Language Models (LLMs) have also been applied in climate change research. In [7], for instance, researchers collected 360,000 abstracts from climate scientists and fine-tuned GPT-2 to create ClimateGPT-2, aiding researchers, policymakers, and climate stakeholders in understanding complex climate-related knowledge.

Climate change introduces challenges like overheating and poor air quality in buildings, which can negatively impact occupants' health, especially elderly or ill individuals [11]. Automated Fault Detection Diagnosis (AFDD) has been proposed in some studies to improve

HVAC energy efficiency. For example, deep learning has been applied to Air Handling Units (AHUs) [12] to enhance energy management and reduce environmental impact, minimizing manual interventions.

Research in [13] highlights the substantial environmental impact of man-made building materials and emphasizes the importance of evaluating these impacts during construction. However, challenges such as the lack of established indicators and weighting systems remain. The Building Research Establishment Environmental Assessment Method (BREEAM) is widely adopted for environmental assessment purposes.

Thermal conditions within buildings, including heat exposure, have been studied by analyzing indoor and outdoor temperature and relative humidity relationships. In [14], a case study in Nigeria investigated thermal conditions in houses with two types of windows over three years. Findings revealed substantial indoor temperature and humidity variations and an inverse relationship with outdoor conditions. Houses with louver-type windows experienced lower indoor temperatures compared to those with sliding windows [14]. Further experiments have explored the impact of humidity on human comfort and productivity, as shown in [15], where optimal relative humidity levels (30%-60% RH) were found essential for health, stress reduction, and productivity.

A study conducted in Cairo examined the use of cool paving as an alternative strategy to reduce air temperatures and buildings' energy demands across areas with varying densities (25%, 50%, and 85%) [16]. This study emphasized the importance of cool materials, such as cool pavements, in mitigating urban heat island effects and reducing cooling energy consumption.

Building materials are also affected by pollutants like sulfur dioxide, nitrogen oxides, chlorides, carbon dioxide, and ozone. R.N. Butlin [17] identified the types of air pollutants that damage buildings and assessed the associated costs. Research has also examined the effects of air pollution on historical landmarks and monuments. In [18], a study assessed the effects of air pollution and meteorological factors on historical monuments in India, noting fluctuations in outdoor air quality and inadequate ventilation as factors that degrade indoor air quality.

Air pollution initiates numerous physical, chemical, and biological reactions that negatively affect buildings and residents' health. In [19], a detailed review quantified the effects of various air pollutants on building materials. Additionally, LLMs have been used to gather insights into climate change emissions. In [20], an LLM was fine-tuned on Climate Watch emissions data [21] for precise emissions information at global and country levels. Related work has gathered data from sources like academic publications and patent databases, discussing LLMs' role in climate innovation and policy research [22]. These models have also been used to address questions related to climate change and finance issues [23].

Another review on the outdoor environment's effects on the indoor thermal environment showed that the exchange of outdoor heat and the infiltration of pollutants significantly impact building efficiency, indoor air quality, and comfort. In [24], a study found that increasing tree coverage by 17% during the hottest summer months can lower indoor temperatures by 1.1°C. The study also highlighted the effects of air pollutants on indoor environments and energy consumption; for instance, climate change may cause a 223%-1050% increase in cooling and heating energy demands by 2050. Additionally, for every 75μg/m^3 increase in PM2.5 concentration, average power consumption could rise by 11.2%. The research focused on conclusions from analyzing outdoor and indoor environmental factors.

Material and Methods:

Data Collection:

Environmental impacts are influenced by numerous factors within this broad domain. This research specifically targets key parameters—temperature, humidity, and air quality index—to understand their effects on buildings and indoor environments. A range of resources was consulted, including research papers, articles, specialized solution providers' websites (as referenced in Sections 0.2.1, 0.2.2, and 0.2.3), and expert insights, to gather comprehensive information. This information was then used to create a dataset of textual documents, designed for input into Large Language Models. These documents include both impact analysis and recommendations, compiled through systematic review and selection from the aforementioned sources. Figure 1 illustrates the data collection and compilation process: information was first gathered from multiple sources (referenced in Sections 0.2.1, 0.2.2, and 0.2.3), focusing on knowledge related to temperature, humidity, and air quality. Text documents were then created and combined to generate detailed, compiled reports.

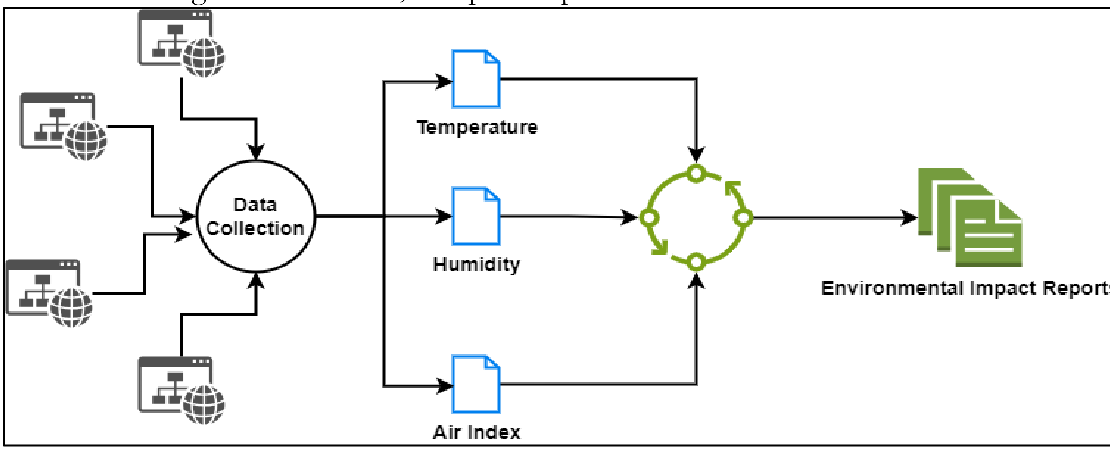


Figure 1. Data Collection Process Pipeline

Analysis of Temperature and GHGs:

According to data from the National Centers for Environmental Information (NCEI) [3], the global average temperature has increased by approximately 2°F (1°C) since the pre-industrial period (1850-1900). To analyze recent trends, we collected average temperature data for the past 10–11 years from NCEI, revealing a temperature rise in Karachi from 2012 to 2023 and from 2014 to 2024, as shown in Figure 2.

Climate Watch Data [21] indicates a significant rise in greenhouse gas (GHG) emissions—specifically CO_2 (carbon dioxide), CH_4 (methane), and N_2O (nitrous oxide)—both globally and within Pakistan from 1992 to 2020. Figure 3 illustrates this increase in emissions, shown in metric tons, highlighting the growing environmental impact of these gases.

Compiling and Constructing Impact Information:

After extensive information gathering from various sources [17] [18] [15] [24] [25] [11], we compiled the findings into text files detailing the impacts of specific environmental parameters—temperature, humidity, and air quality index—on buildings, indoor environments, and residents. Additionally, we included recommendations for mitigating these impacts. Each parameter (temperature, humidity, and air quality index) was categorized based on intensity levels such as High, Low, and Moderate, with each category containing at least 2–3 text files. Given multiple files for each impact category and multiple intensity categories, we generated a diverse range of combinations, ultimately producing approximately 4,000 text-based reports.

Air Pollution:

Air pollution, including particulate matter (PM2.5 and PM10) and harmful gases like sulfur dioxide (SO_2), is a major factor contributing to climate change and global warming [18]. These pollutants impact building structures; for instance, SO_2 can cause surface erosion and metal corrosion through acidic reactions, forming damaging crusts [17]. Indoor environments are also vulnerable, where pollutants compromise air quality and pose health risks for residents [11]. Understanding the current air quality index, its effects, and methods to reduce exposure is essential for effective mitigation. Key resources used for air pollution information include [17]

[18] [19] [26] [27] [28] [29], and air quality index levels were defined based on OpenWeather's concentration scale (µg/m³) in Table 1 [30].

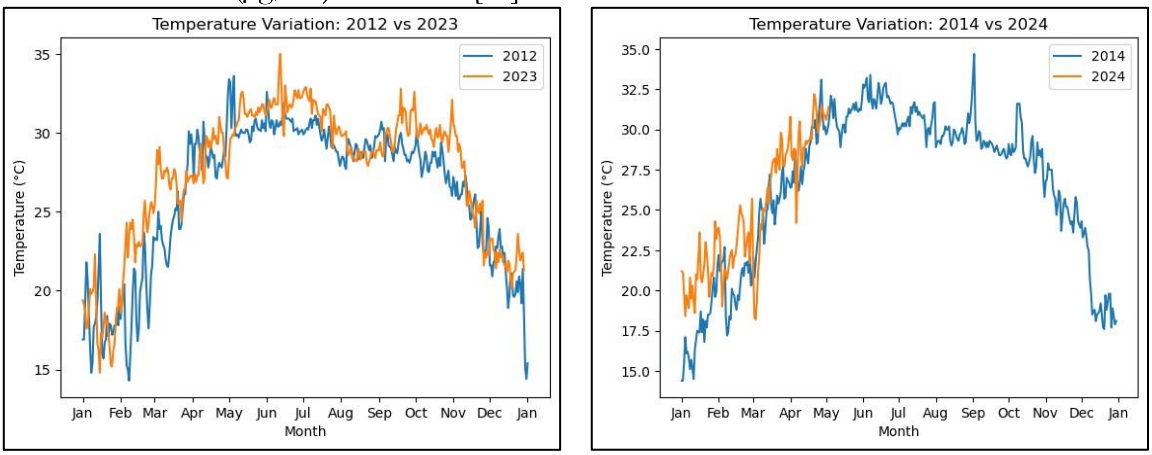
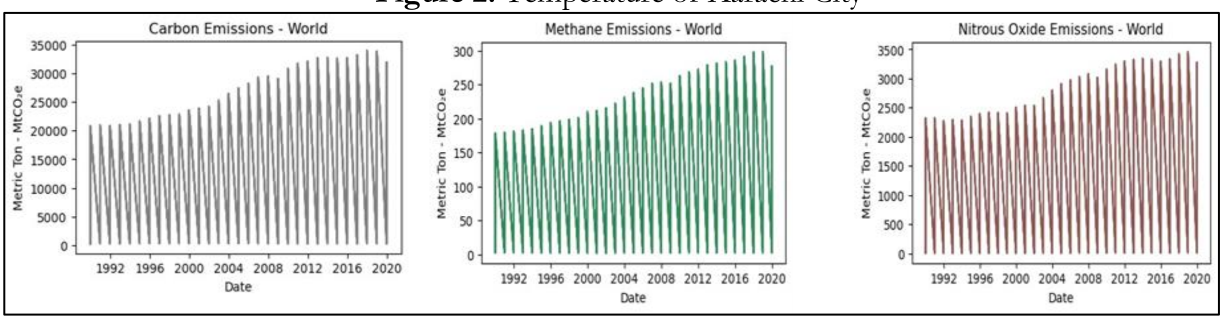
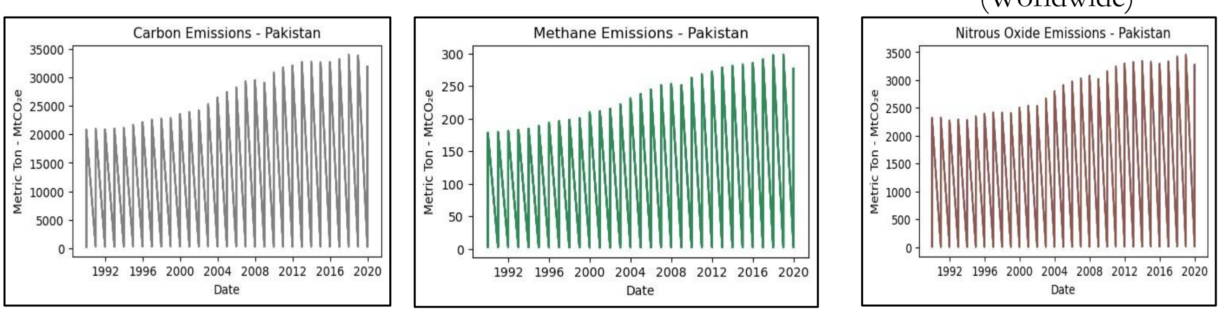


Figure 2. Temperature of Karachi City



(a) CO_2 Emission (Worldwide) (b) CH_4 Emission (Worldwide) (c) N_2O Emission (Worldwide)



(d) CO_2 Emission (Pakistan) (e) CH_4 Emission (Pakistan) (f) N_2O Emission (Pakistan)

Figure 3. Greenhouse Gas Analysis

Humidity:

Humidity also affects building integrity and occupant health. High humidity can shorten building lifespan, promote mold growth, increase indoor moisture, and degrade air quality, impacting resident comfort and productivity [15] [24]. To compile information on humidity's effects, we referenced data from sources including [15] [24] [14] [31] through [44] [25] [11]. Table 2 shows the humidity ranges used for this study.

Temperature:

Recent temperature rises, shown in Figure 2, correlate with increased greenhouse gas emissions, especially carbon dioxide, which both drives and results from higher temperatures [45] [46] [11]. Elevated temperatures lead to heat retention, increased energy use, material expansion and contraction, and potential building damage, impacting indoor conditions and resident well-being.

In this study, 0°C was used as the minimum temperature benchmark for Karachi. Temperature conditions were categorized as high, low, and very low, based on historical climate data specific to Karachi, sourced from the Weather Atlas website [47]. This categorization aligns with local climate conditions, ensuring relevance and accuracy. More details are available in sources [25] [11] [24] [48] through [57]. Temperature levels are outlined in Table 3.

Table 1. Air Quality Index levels [30]

Qualitative Name Index	SO_2	NO_2	PM_{10}	$PM_{2.5}$	O_3	CO
Good	[0; 20)	[0; 40)	[0; 20)	[0; 10)	[0; 60)	[0; 4400)
Fair	[20; 80)	[40; 70)	[20; 50)	[10; 25)	[60; 100)	[4400; 9400)
Moderate	[80; 250)	[70; 150)	[50; 100)	[25; 50)	[100; 140)	[9400; 12400)
Poor	[250; 350)	[150; 200)	[100; 200)	[50; 75)	[140; 180)	[12400; 15400)
Very Poor	≥350	≥200	≥200	≥75	≥180	≥15400

Table 2. Humidity Levels [14][44][43][37][31]

Humidity	Range (%)
Very High	Above 70%
High	61%-70%
Optimal	40%-60%
Moderate	30%-39%
Low	Below 30%

Transformers:

The introduction of Transformers [10] has revolutionized natural language processing (NLP), particularly in tasks such as text generation, translation, and summarization. Traditional models like Recurrent Neural Networks (RNNs) and Long Short-Term Memory Networks (LSTMs), including their variants like Gated Recurrent Units (GRUs), often struggle with capturing long-term dependencies in sequences. In contrast, Transformers leverage encoder and decoder layers combined with self-attention mechanisms to process entire sequences simultaneously, allowing them to effectively maintain context across long sequences.

Large Language Models (LLMs), such as GPT-2 and LLAMA-2-7B, significantly enhance the capabilities of Transformers. By fine-tuning these pre-trained models for specific tasks, they can generate coherent, contextually relevant text that aligns with the requirements of the task at hand.

GPT-2:

GPT-2 (Generative Pre-trained Transformer 2) is an autoregressive large language model (LLM) with 1.5 billion parameters, trained on a vast dataset known as Web Text, which contains approximately 8 million web pages. The model consists of multiple layers of decoders, each equipped with self-attention mechanisms and feed-forward neural networks. The key components of GPT-2 include the self-attention mechanism, which allows the model to understand context, and feed-forward neural networks, which help capture complex patterns in the data [9].

Table 3: Temperature Levels [47]

Temperature	˚C
Very High	Above 40˚C
High	30˚C - 39˚C
Moderate	25˚C - 29˚C
Comfortable (Optimal)	20˚C - 24˚C
Low	10˚C - 19˚C
Very Low	0˚C - 9˚C

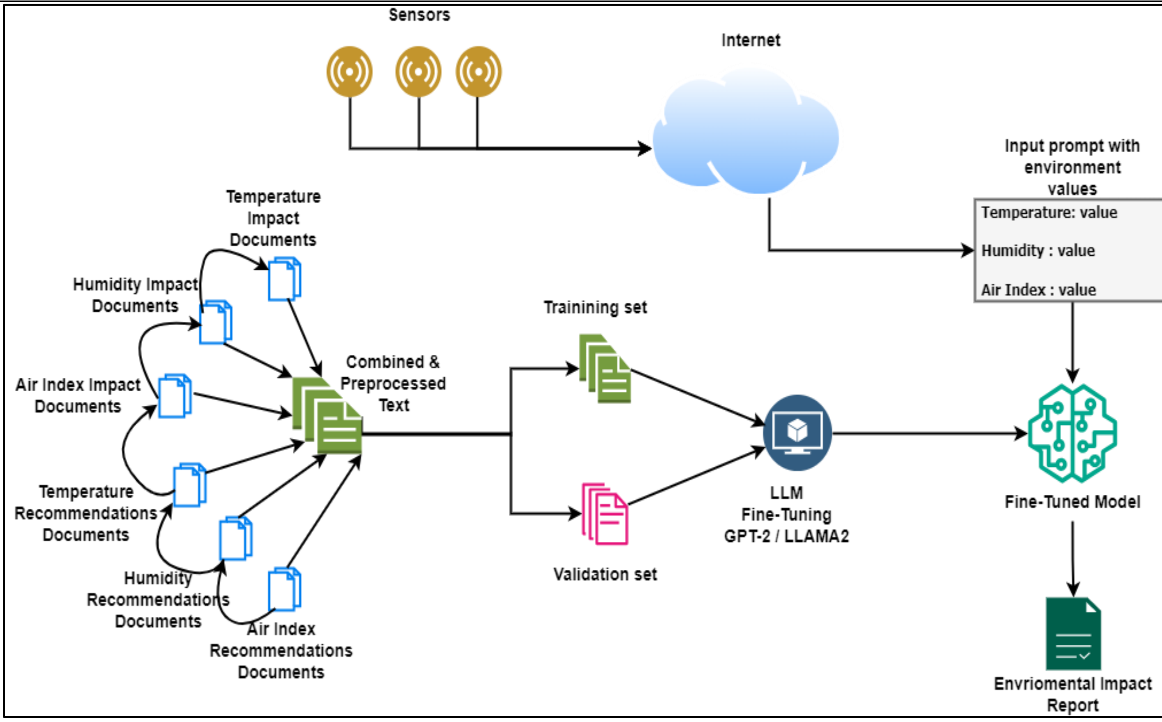


Figure 4. Proposed work methodology

LLAMA2-7B:

LLAMA2-7B (Large Language Model Meta AI 2) [8] is a highly capable language model with 7 billion parameters, significantly surpassing GPT-2's 1.5 billion parameters. The LLAMA2 models are trained on a unique blend of publicly accessible online data and employ advanced methodologies, including Supervised Fine-Tuning (SFT) and Reinforcement Learning with Human Feedback (RLHF), to improve performance. With 7 billion parameters, LLAMA2-7B is designed to capture more nuanced patterns and better understand context in text, enabling more accurate and relevant text generation [8].

Methodology:

After gathering, pre-processing, and compiling the data into the textual reports dataset discussed in section 0.2, we fine-tuned the Large Language Models (LLMs) mentioned in sections 0.3.1 and 0.3.2—namely, Generative Pre-Trained Transformer 2 (GPT-2) and Large Language Model Meta AI 2 (LLAMA2-7B) from Nous Research, specifically the Nous Research/Llama-2-7b-hf version available on Hugging Face. To generate the reports, the model requires input parameters, which include numeric values for temperature, humidity, and air quality index obtained from the Open Weather API [30]. Using these values, the system creates a prompt and passes it to the LLM for report generation. Figure 4 illustrates the methodology employed in this study.

GPT-2 prompt	**LLAMA2-7B prompt**
"OUTDOOR ENVIRONMENTAL FACTORS ANALYSIS Outdoor Temperature: [{temp_type}] Outdoor Humidity: [{humid_type}] Outdoor Air Quality Index: [{air_type}] Location: Karachi City"	"Generate the environment impact details based on the following parameters. ### Input: OUTDOOR ENVIRONMENTAL FACTORS ANALYSIS: Outdoor Temperature: [{temp_type}] Outdoor Humidity: [{humid_type}] Outdoor Air Quality Index: [{air_type}] Location: Karachi City ### Response:"

Results and Discussion:

The fine-tuning of both LLAMA2-7B and GPT-2 models** was carried out using textual reports data collected from various sources, as described in Sections 0.2.1, 0.2.2, and 0.2.3. These reports outline the effects of outdoor temperature, humidity, and air quality on buildings, along with recommendations for mitigation strategies. The length of the generated reports ranges from approximately 390 to 780 words.For obtaining real-time values of outdoor temperature, humidity, and air quality, the Open Weather API [30] was utilized.

LLM Fine-Tuning:

GPT-2 and LLAMA2-7B (Nous Research/Llama-2-7b-hf version from Hugging Face) were fine-tuned using the parameters outlined in Tables 4 and 5. LLAMA2-7B, due to its larger size, demonstrates superior efficiency in handling more complex language tasks. To further enhance its performance, Low-Rank Adaptation (LoRA) was applied, reducing the number of trainable parameters by approximating weight matrices with low-rank representations. Additionally, Parameter-Efficient Fine-Tuning (PEFT) methods were used to optimize training, which not only minimizes fine-tuning time but also reduces resource consumption for large models.

Table 4. GPT-2 Parameters

Parameters	Values
Batch size	2
Learning rate	$5e^{-4}$
No. of epochs	30
Optimizer	Adam with $1e^{-8}$
Warm-up Steps	$1e^{2}$
Generated text max length	700
No. of returned sequences	1
n-gram penalty	3

```
OUTDOOR ENVIRONMENTAL FACTORS ANALYSIS:

Outdoor Temperature: 26 degree celcius
Outdoor Humidity: 40%
Outdoor Air Quality Index: 2
Location: Karachi City

*IMPACT FACTORS*

A. TEMPERATURE:
* The current outdoor temperature (26) degree celsius is moderate, which poses a less severe threat to buildings compared to extreme heat levels. However, prolonged exposure to moderate temperatures can still cause damage to building materials, especially if the temperature is fluctuating.

* This moderate temperature is beneficial for the building and minimizes the risk of heat-related damage. However, it's essential to maintain indoor thermal conditions to optimize comfort for occupants.

B. HUMIDITY:
* The current outdoor humidity level (40) percentage is optimal, providing a favorable indoor environment for occupants and minimizing the risk of damage to materials from high humidity.

* This level ensures a healthy indoor atmosphere, with optimal air quality and comfort for occupants. The building infrastructure is protected from harmful effects of high humidity, and maintenance costs for humidifiers and dehumidifiers are typically minimal.

C. AIR QUALITY:
* The current outdoor air quality index (2) indicates fair air quality, which is acceptable for both buildings and humans.

* Fair air quality offers moderate protection to building materials, with pollutants including sulfur dioxide (SO2) (>80 µg/m3), nitrogen dioxide (NO2) (>65 µg/m3), and ozone (O3) (>100 µg/m3) present at levels that are not as high as those during hazardous air pollution periods, but still impacting their lifespan. For example, the speed of rust formation on average is slowed compared to during periods of poor air quality. However, fair air quality conditions can still contribute to the deterioration of building materials in urban areas, particularly in polluted urban air sheds. The impact includes various effects such as surface erosion, crust formation, and corrosion of various materials including metals, concrete, and wood. This ongoing corrosion process contributes to structural weakening and maintenance issues over longer periods. Despite this slower rate of deterioration compared to during hazardous air quality episodes, fair air quality conditions nevertheless foster the proliferation of harmful bacteria on surfaces, further exacerbating indoor air quality and posing health risks for occupants and building visitors.


*RECOMMENDATIONS*

A. TEMPERATURE:
* Ensure proper ventilation of kitchens and washrooms to prevent moisture accumulation, which can lead to mold growth.
* Consider planting drought-tolerant plants around your home to conserve water.

* Heat recycling units are recommended.

B. HUMIDITY:
* Natural ventilation is recommended to maintain humidity levels in the home.
* Ensure proper air ventilation in kitchens and bathrooms to prevent moisture build-up, which can lead to mold growth and compromised building quality.

* No treatments are required. Natural air circulation is sufficient.

C. AIR QUALITY:
* Consider using a purifier with a HEPA filter to remove pollutants from indoor air.
* Regularly maintain your car and its components to ensure its health and longevity.

* Keep monitoring indoor air quality with sensors.
```

Figure 5. Generated Report by LLAMA2-7B

Table 5. LLAMA2-7B Parameters

Parameters	Values
Batch size	4
Learning rate	$1e^{-2}$
No. of epochs	2
Optimizer	Adamw32bit
Warm-up ratio	0.05
Evaluation steps	0.2
Generated text max length	1000
No. of returned sequences	1

Model Outcomes:

LLAMA2-7B produces more refined and superior output results compared to GPT-2, particularly in terms of word variation and knowledge diversity. Figure 5 illustrates a generated report from LLAMA2-7B for a temperature of 26°C (Comfortable), humidity of 40% (Optimal), and an air index of 2 (Fair). The report details the environmental impacts on buildings and provides recommendations for minimizing these effects.

Evaluation Metrics:

Evaluating LLMs requires specialized metrics that differ from traditional machine learning models. The following metrics were used for evaluation:

Recall-Oriented Understudy for Gusting Evaluation (ROUGE):

This metric is used for text summarization and calculates recall by comparing the overlap of n-grams between generated and reference texts. ROUGE-L specifically measures the longest common subsequence, making it suitable for various text generation tasks [58].

Bilingual Evaluation Understudy (BLEU):

BLEU evaluates translation and summarization by matching n-grams between generated and reference texts, with a focus on precision [59].

Metric for Evaluation of Translation with Explicit Ordering (METEOR):

METEOR is a more comprehensive metric than BLEU and ROUGE, as it calculates both precision for matching n-grams and recall for overlapping n-grams, while also considering synonyms, stemming, and paraphrasing [60].

While ROUGE and BLEU have limitations, such as comparing word-to-word matches without capturing context or synonyms, METEOR improves upon this by incorporating synonyms for diversity. However, it still struggles to capture context effectively.

BERT Score:

BERT Score evaluates text by using contextual embeddings from Bidirectional Encoder Representations from Transformers (BERT). Unlike BLEU and ROUGE, which rely on exact token matches, BERT Score focuses on semantic meaning by comparing contextual embeddings. It computes precision, recall, and F1 scores for more accurate evaluations, offering a more nuanced understanding of text compared to traditional n-gram metrics. BERT Score is less sensitive to word order and effectively handles synonyms [61].

Table 6 shows the evaluation metric scores for the generated text from LLAMA2-7B, as seen in Figure 5, using three reference texts with the same input parameters. Figure 6 visualizes the comparison of evaluation metrics (BLEU, ROUGE-L, METEOR, and BERT Score), highlighting BERT Score's superior ability to understand semantic meaning.

Table 6: BERT Scores

Ref Text	Rouge L	Bleu	Meteor	BERT Score
1	0.3709	0.3036	0.4482	0.9158
2	0.3563	0.2941	0.4233	0.9109
3	0.3538	0.2873	0.4343	0.9098

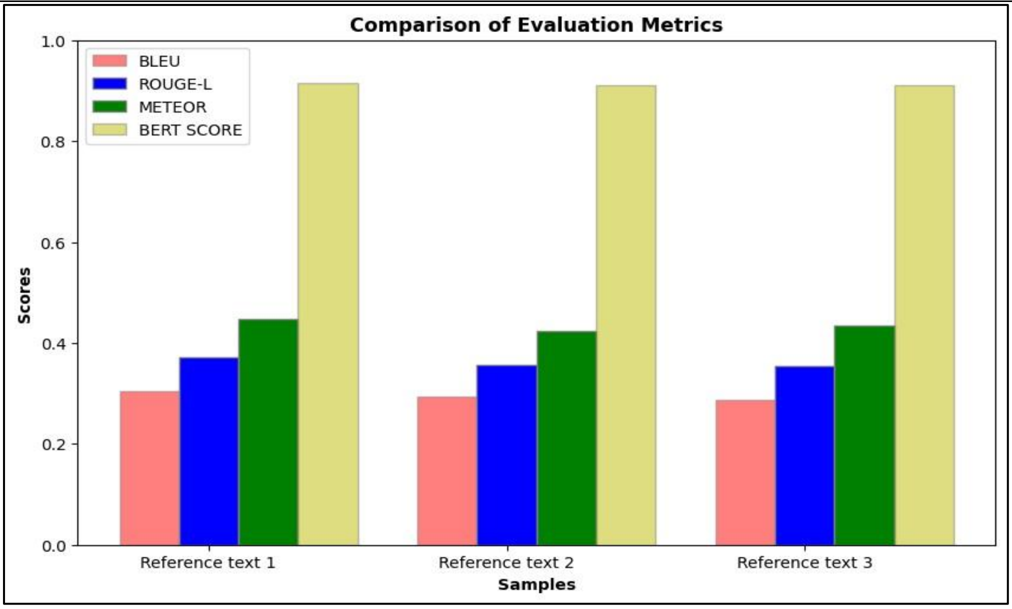


Figure 6. Evaluation metrics scores

Evaluation Graphs:

Generative Pre-trained Transformers 2 (GPT-2)

Figure 7 shows the visualization of training loss and validation loss of GPT-2 that is given below:

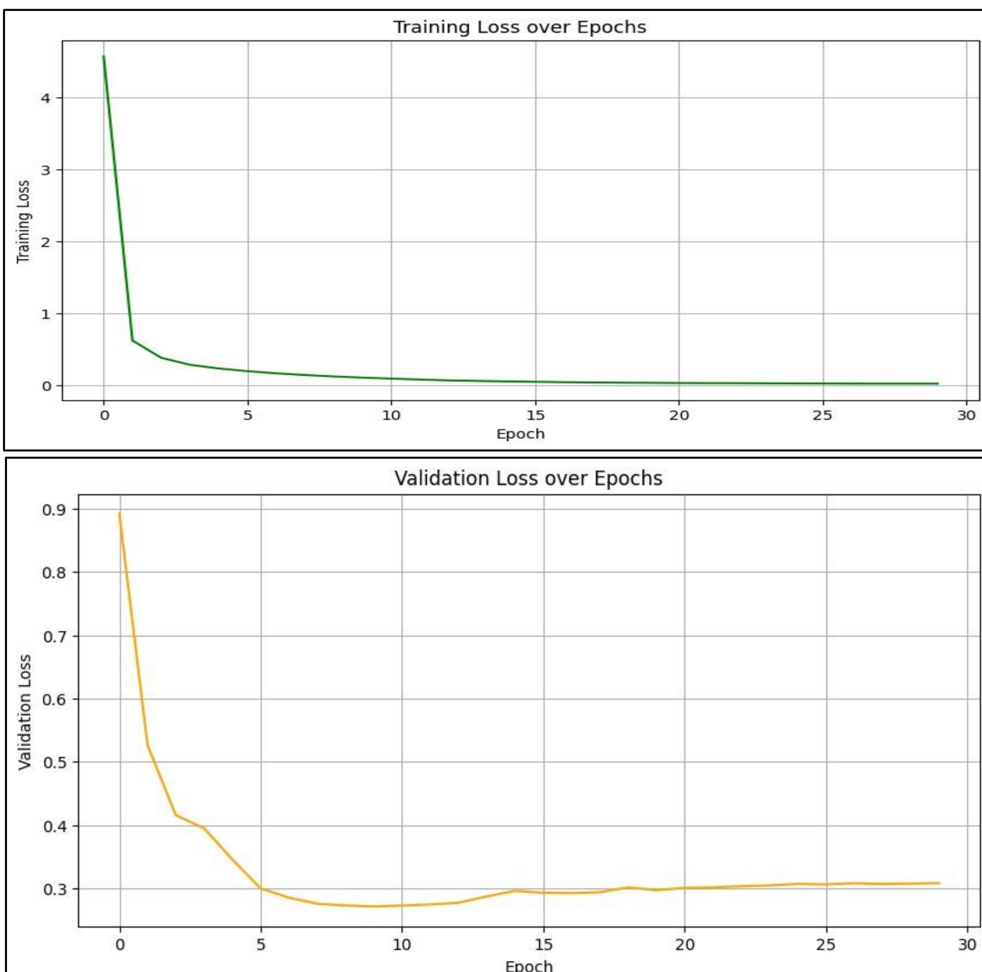
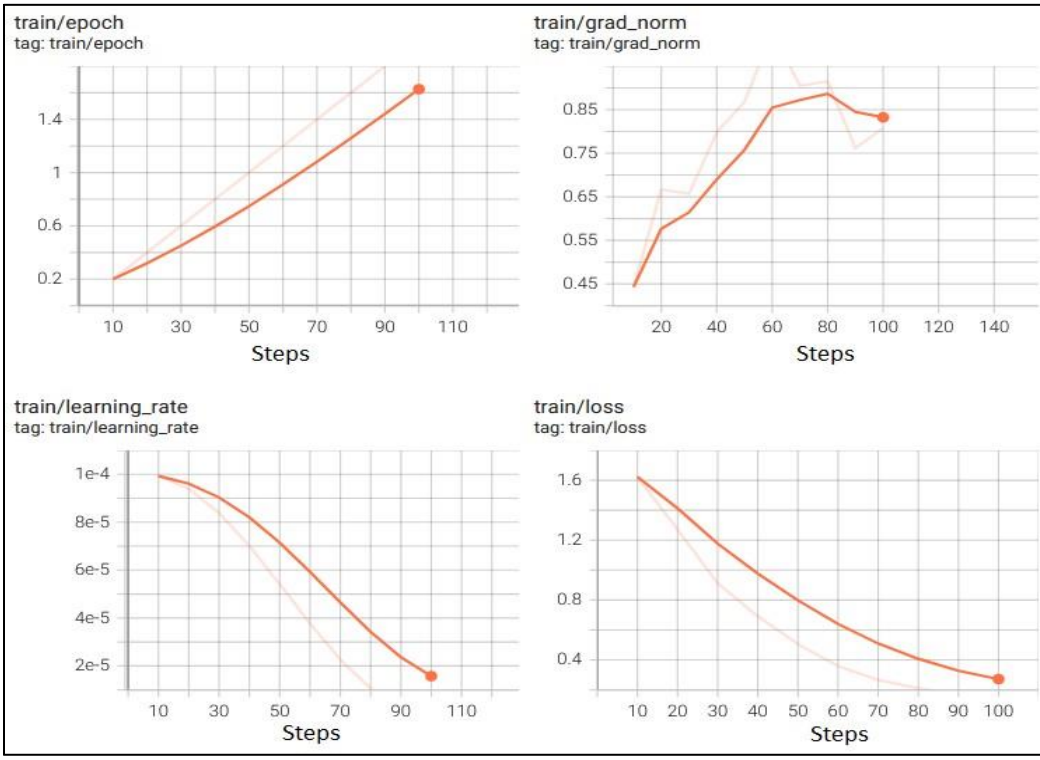


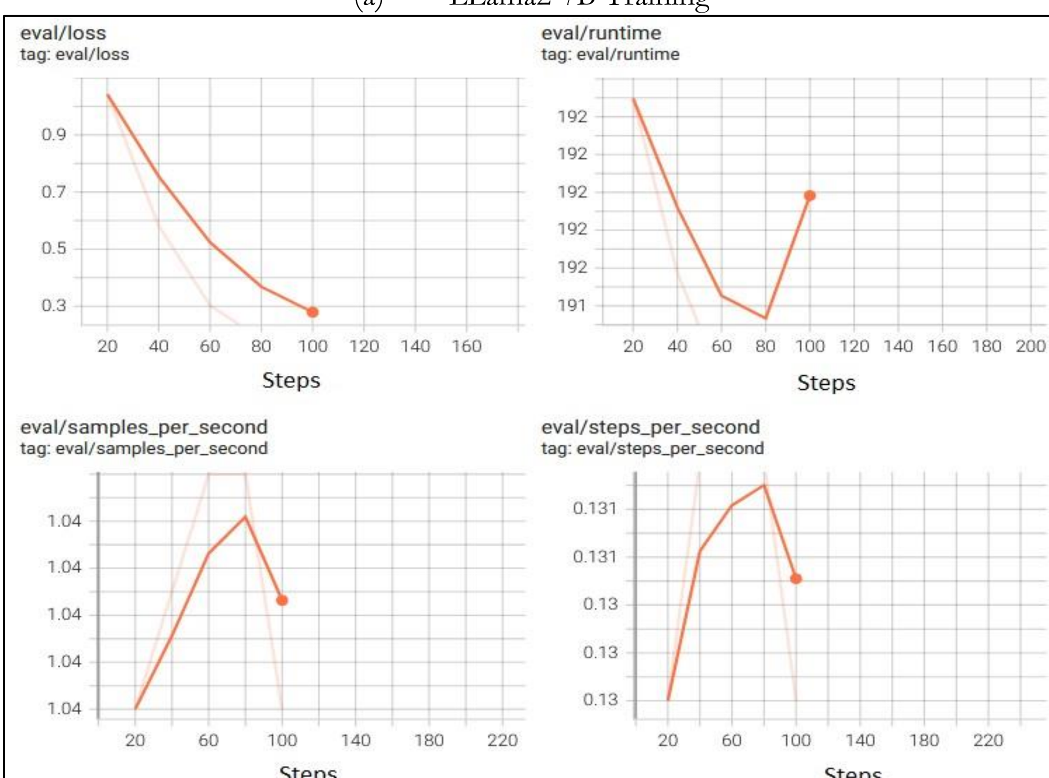
Figure 7. GPT-2 Training and Validation

Large Language Model Meta AI 2 (LLAMA2-7B):

Tensor Board provides a comprehensive visualization of training metrics with a smoothing value of 0.6 by default, aiding in the analysis. Figure 8 shows the training and validation execution details of LLAMA2-7b.



(a) LLama2-7B Training



(b) LLama2-7B Validation

Figure 8. Training and Validation Graphs

Conclusion and Future Directions:

This work presents research and analysis of outdoor environmental factors—namely temperature, humidity, and air quality index—and their impact on buildings. We gathered information from a variety of sources, including articles, research papers, blogs, and specialized service provider websites. The findings were then compiled into textual reports that detail these impacts and provide mitigation recommendations. In addition, we analyzed historical temperature data and CO2 emissions both in Karachi and globally, highlighting a consistent increase in values, as shown in Figures 2 and 3. These reports were used to fine-tune Large Language Models (LLMs), which were trained to generate text that helps residents understand and mitigate the effects of the outdoor environment on buildings. The LLMs clarify the complex relationship between environmental factors and building structures, contributing to more effective urban planning and sustainable development.

For future research, we plan to investigate the impact of pollutants such as CO2, CH4, N2O, chlorofluorocarbons, and others on both building structures and indoor environments. We will explore how different types of buildings respond to these pollutants and work to develop strategies that minimize their effects. Additionally, we aim to assess how indoor environments contribute to global warming and increased greenhouse gas emissions, with a focus on strategies to mitigate these impacts. Future reports will also evaluate how indoor conditions contribute to climate change and global warming, offering actionable recommendations for minimizing these effects. This ongoing research will monitor indoor parameters such as temperature, humidity, and air quality index, extending our current analysis of outdoor environmental factors.

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