Disease Detection Using Wrist Pulse Analysis

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Citation | Ali. F, Rehman. S, Ayaz. A, Ahmad. A. M, "Disease Detection Using Wrist Pulse Analysis", IJIST, Vol. 07 Special Issue. pp 50-61, May 2025
Received | April 07, 2025 **Revised |** May 04, 2025 **Accepted |** May 05, 2025 **Published |** May 06, 2025.

Early detection of diseases is crucial for effective treatment and management. Traditionally, disease detection involves invasive and costly medical procedures. However, recent advancements in non-invasive methods have proven highly successful in identifying various illnesses. The wrist pulse has long been an important tool for detecting diseases, with traditional Chinese medicine making extensive use of this method. It shows great promise in diagnosing a wide range of conditions. This study provides a detailed analysis of research on wrist pulse analysis and its applications in disease detection. It examines the physiological basis of wrist pulse analysis, focusing on the relationship between underlying medical conditions and the characteristics of wrist pulses. Additionally, the study explores how wearable pulse detectors and machine learning algorithms can improve the accuracy and effectiveness of wrist pulse analysis. In this research, we use a dataset of 300 samples from various diseases, analyzing it with MATLAB and applying ensemble learning algorithms. We have achieved accuracies above 80% for nearly all algorithms, and accuracy can be further improved by expanding the dataset with more samples and extracting additional features.

Keywords: Wrist Pulses, Wrist Pulse Analysis, Disease Detection, Pulse Signal Processing and analysis, Machine Learning.

Introduction:

Looking, listening, inquiring, and feeling wrist pulses are some of the methods used in traditional Chinese medicine (TCM), a practice that has been around for centuries. The wrist pulse diagnosis, a key component of TCM, is simple, easy to perform, and has no harmful side effects. In Western medicine, wrist pulse diagnosis is explained through blood flow in the body. For example, a person's pulse may feel different if they have lung cancer due to changes in the lungs. Although it requires deep knowledge and experience, TCM doctors typically use three fingers to assess the pulse at several points on the wrist. Over time, researchers have enhanced the accuracy, precision, and reliability of pulse diagnosis by incorporating advanced technologies like Artificial Intelligence and Machine Learning. Based on the way blood circulates throughout the body, this method has gained importance in medical exams. Thanks to advancements in wearable technology, smart devices can now monitor pulses at home. To assist in diagnosing certain illnesses, we have developed a method for analyzing wrist pulse data [1].

Figure 1. Different parts of a wrist pulse

Wrist Pulse and its Parts:

The wrist pulse is a core element of traditional Chinese medicine (TCM), consisting of three distinct points: Cun, Guan, and Chi. Each point provides valuable insights into an individual's health. Doctors carefully evaluate the strength, rhythm, and quality of the pulse at these specific areas of the wrist. Chi represents the pulse of the deep layer, Guan reflects the pulse of the medium layer, and Cun corresponds to the pulse of the shallow layer. By palpating these areas, practitioners can detect subtle changes that may indicate underlying medical conditions or imbalances in the body [2].

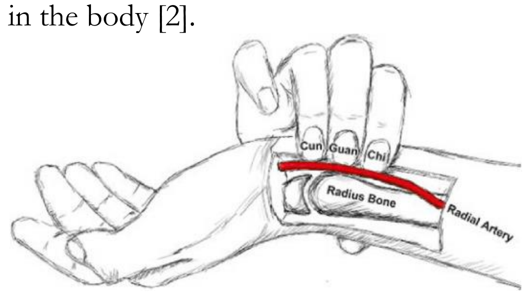

Figure 2. Illustration of different parts of wrist pulse

The Chi or Vata:

In Ayurvedic medicine, Vata is a combination of Ether and Air. It plays a crucial role in two main areas: movement in the body and mind, and communication. Vata helps muscles move, nerves function, and keeps our thoughts and emotions flowing. When Vata is out of balance, it can lead to restlessness, anxiety, and other issues. Therefore, maintaining a balanced Vata is essential for staying healthy and feeling well. The Vata component is characterized by certain distinct traits, such as irregular rhythm patterns, 80-90 bpm, fast, weak, cold, and light in weight [3].

The Guan or Pitta:

In Ayurvedic medicine, Pitta is a combination of Fire and Water and is associated with functions like digestion and metabolism. When Pitta becomes unbalanced, it can cause problems with vision, digestion, and metabolism, especially as people age. The pulse related to Pitta typically has a regular rhythm with a strong beat, usually around 70-80 beats per minute. Pitta is also linked to heat and moisture in the body. On the other hand, Kapha is a mix of Earth and Water, focusing on the body's structure and fluid balance. When Kapha is out of balance, it can lead to issues like congestion, poor taste and smell, back pain, and weight gain, particularly in childhood [4].

The Cun or Kapha:

Kapha manifests in the pulse as a steady rhythm, beating around 50-60 times per minute, moving slowly and smoothly. In Ayurveda, Vata, Pitta, and Kapha control our body, mind, soul, and spirit. Checking the pulse at the wrist is a unique method in Ayurveda that helps assess a person's health and identify any underlying issues. The pulse wave, similar to a pressure signal, can be felt at various locations such as the foot, wrist, or neck. However, it is typically checked at the wrist because it is easily accessible and provides accurate results. This pressure signal is created when the heart contracts and relaxes, pushing blood through the arteries. By examining this signal, we can gain valuable insights into a person's health, both the positive aspects and any potential problems [3].

Machine Learning Models:

1. **XGBoost**: XGBoost (Extreme Gradient Boosting) is an optimized version of gradient-boosted decision trees, designed for speed and performance. It incorporates regularization techniques to prevent overfitting and handles missing values efficiently. Hyperparameters for XGBoost were optimized using Randomized SearchCV [5].
2. **LightGBM**: LightGBM (Light Gradient Boosting Machine) is a tree-based learning algorithm known for its efficiency and scalability. It can handle large datasets with high-dimensional features. LightGBM uses a histogram-based approach to determine optimal splits, speeding up training and reducing memory usage. Randomized SearchCV was used for hyperparameter tuning [6] .
3. **Gradient Boosting Classifier**: This method is used for regression and classification tasks, addressing the limitations of previous models in a step-by-step manner. Although it can be computationally intensive, it is highly effective. Randomized SearchCV was applied to fine-tune the model's hyperparameters [7].
4. **Hist Gradient Boosting Classifier**: This variant of the Gradient Boosting Classifier uses histogram-based techniques to speed up training and prediction. It is particularly effective for high-dimensional data, making it well-suited for large datasets. Randomized SearchCV was used for hyperparameter adjustment [8].
5. **Stacking Classifier**: We utilized a stacking classifier, which combines multiple base models to improve prediction accuracy. The stacking framework feeds the outputs of various machine learning models (base learners) into a meta-classifier, which generates the final prediction. By leveraging the strengths of multiple classifiers, this ensemble approach reduces overfitting and enhances generalization [9].

Objectives of the Study:

- To develop a non-invasive method for detecting potential health conditions by analyzing wrist pulse signals.
- To preprocess wrist pulse data from healthy and diseased individuals for machine learning analysis.
- To extract relevant features (e.g., pulse waveforms, rate, amplitude, variability) from the wrist pulse signal.

- To apply and evaluate machine learning algorithms for classifying disease states based on wrist pulse characteristics.
- To build a predictive model capable of distinguishing between normal and abnormal pulse patterns related to specific diseases.
- To compare model performance using accuracy, precision, recall, and other evaluation metrics to identify the most effective algorithm.
- To explore the potential of wrist pulse analysis as a low-cost, portable diagnostic tool for remote or under-resourced healthcare settings.

Methodology:

Data Collection:

The dataset used in this study is publicly available at (https://www4.comp.polyu.edu.hk/~cslzhang/Pulse_datasets.htm) which consists of 300 wrist pulse signal samples in MATLAB (.mat) format, categorized into five classes:

- Normal (100 samples)
- Pancreatitis (54 samples)
- Diabetes Mellitus (DBU) (77 samples)
- Appendicitis (35 samples)
- Acute Appendicitis (54 samples)

For further analysis, various features were extracted from the time series data, including basic statistical features, frequency domain characteristics, rolling statistics, autocorrelation, entropy, and advanced statistical features generated from rolling windows. These features were then fed into machine learning models to enhance classification accuracy.

Feature Extraction:

Key features were extracted from the pulse signals using the statistical methods, including waveform morphology, frequency, pulse amplitude, and statistical parameters. Preprocessing steps, such as normalization and noise filtering, were applied to the signals. The extracted features included:

- Time domain features: mean, median, mode, standard deviation, min, max, skewness, and kurtosis, which provide insights into the overall intensity and spread of the signal.
- Frequency domain features: rolling mean, rolling median, and rolling mode.

These features were calculated to summarize the signal's overall shape and variability; Autocorrelation features were also considered to analyze periodicity and temporal dependencies in the wrist pulse signals. Among the features, the rolling mean and standard deviation are the most significant, as they capture the fundamental structure and to analyze local changes and trends in the signal over time, which are key indicators of health. Additionally, autocorrelation features were employed to examine repeating patterns and temporal dependencies within the pulse signal, which are often linked to cardiovascular health. Among all features, the rolling mean and standard deviation proved particularly significant, as they effectively captured the underlying rhythm and fluctuations in the pulse signal—factors that are often indicative of potential health conditions. These techniques helped in converting raw time-series data into meaningful numerical features that could be fed into machine learning models [10].

Machine Learning Models:

We utilized gradient boosting algorithms for classification, including:

- Hist Gradient Boosting Classifier
- LightGBM
- XGBoost
- Gradient Boosting Classifier

The dataset was divided into training and testing sets according to established rules. Performance indicators, such as accuracy, precision, recall, and F1-score, were used to evaluate the models.

Model Architecture:

In this study, we employed ensemble learning architectures, specifically Gradient Boosting-based models, to detect diseases from wrist pulse signals. The models used—Hist Gradient Boosting Classifier, LightGBM, XGBoost, and Gradient Boosting Classifier—are decision tree ensembles optimized for speed and performance.

Model Validation & Training:

To prevent overfitting and ensure robustness, we used a stratified 10-fold cross-validation technique to train the classifiers on the selected features. The following steps were taken:

1. **Data Splitting**: The dataset was divided into 80% for training and 20% for testing.
2. **SMOTE**: The Synthetic Minority Over-Sampling Technique (SMOTE) was applied to address class imbalance by generating synthetic samples for the minority classes.
3. **Hyperparameter Tuning**: Randomized Search CV was used for hyperparameter tuning, optimizing parameters such as learning rate, maximum depth, and the number of estimators.
4. **Model Training**: The classifiers were trained on the training set using the best hyperparameters identified during tuning.
5. **Model Evaluation**: Each classifier's performance was evaluated on the testing set using accuracy, precision, recall, F1-score, and confusion matrix.

Visualizations of Feature Importance:

The feature importance graphs for each model are displayed in Figures 2.1–2.3. These visualizations highlight which features have the most predictive power in the classification process.

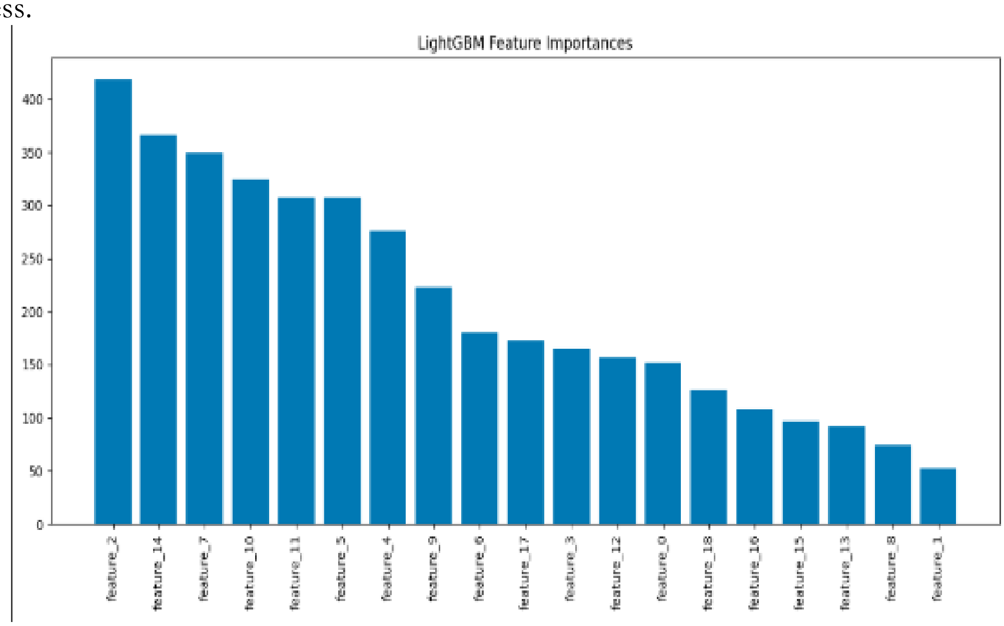

Figure 3. Light GBM Feature Importances

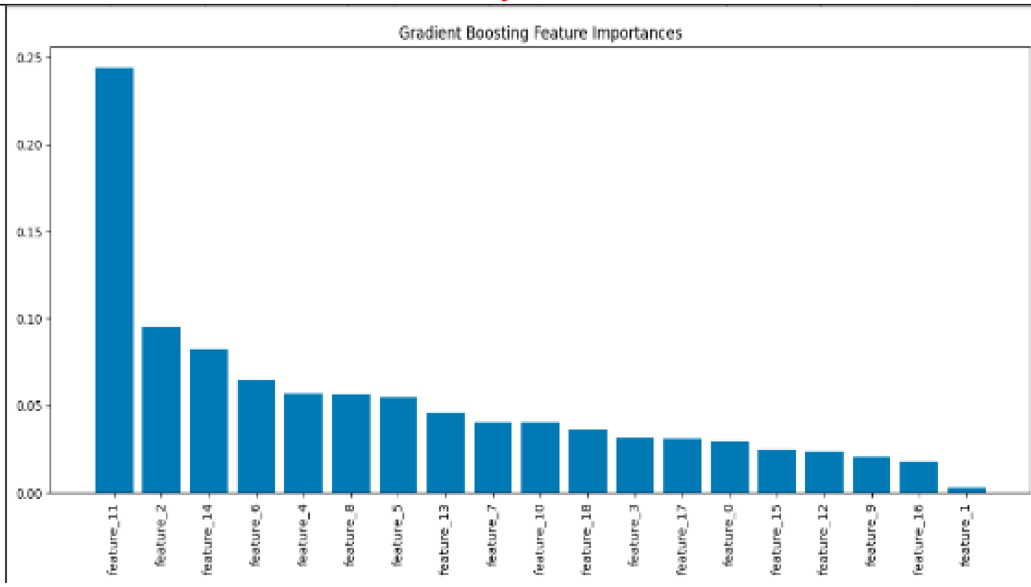

Figure 4. Gradient Boosting Feature Importance

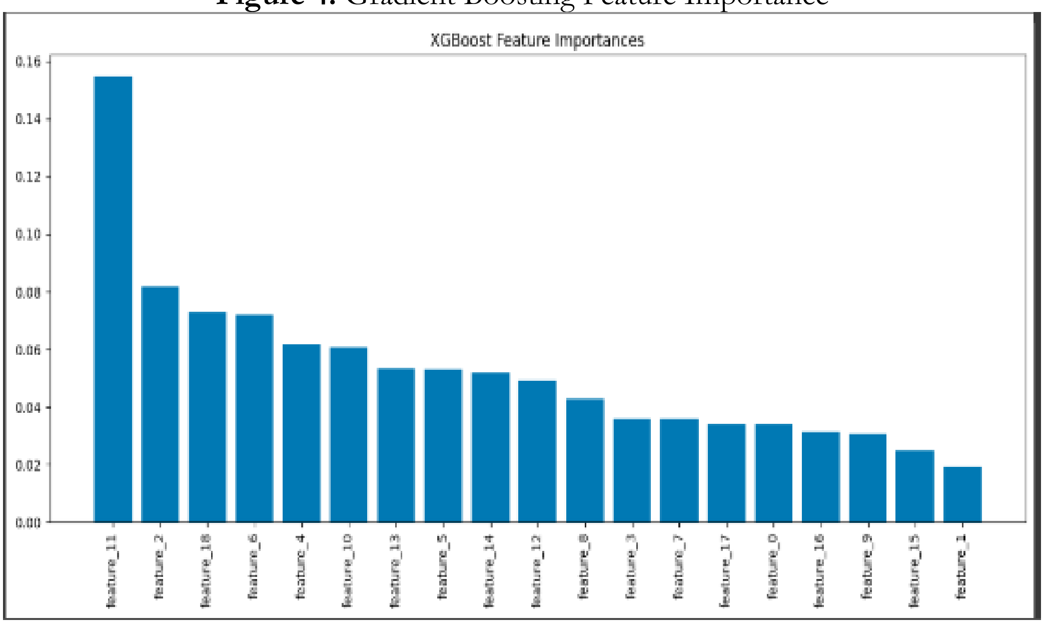

Figure 5. XGBoost Feature Importances

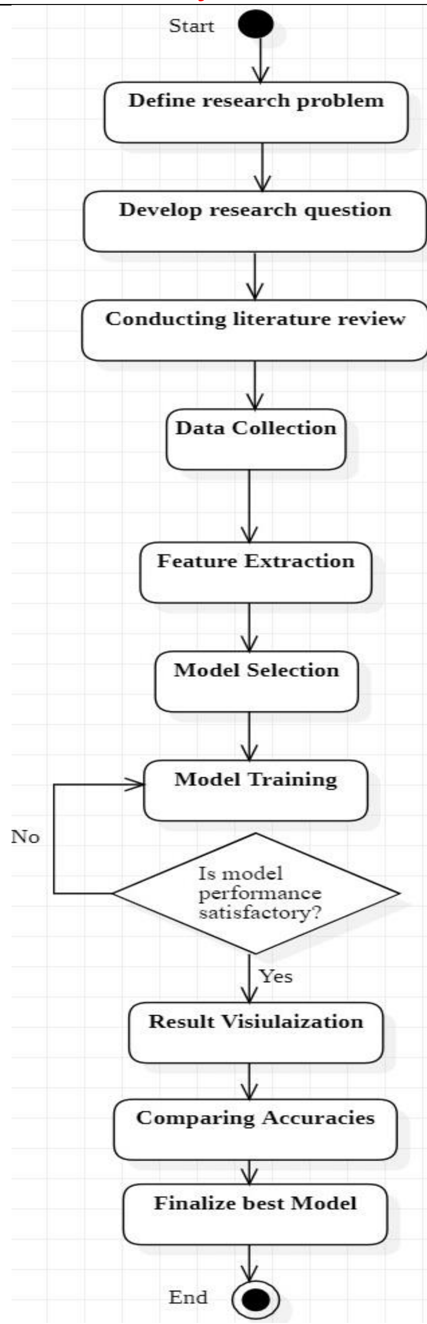

Figure 6. Methodology flow diagram

Results:

Performance Assessment of Classifiers:

Table 1. Results of different classifiers used

Classifier	Accuracy	Precision	Recall	F1-Score
XGBoost	0.83	0.84	0.83	0.89
LightGBM	0.80	0.79	0.80	0.80
Gradient Boosting Classifier	0.78	0.82	0.78	0.88
Hist Gradient Boosting Classifier	0.81	0.83	0.81	0.81
Stacking Classifier	0.80	0.83	0.80	0.80

The performance of the four classifiers—XGBoost, LightGBM, Gradient Boosting Classifier, and Hist Gradient Boosting Classifier—was evaluated based on the methodology discussed earlier. The results of the assessment are summarized in Table 1, which is presented below.

XGBoost Performance:

Among all the classifiers used in this study, XGBoost demonstrated the highest accuracy and F1-score, highlighting its robustness and effectiveness in distinguishing between different medical conditions. Its exceptional performance can be attributed to its ability to handle missing values efficiently and apply regularization techniques to prevent overfitting. As the top performer in this analysis, XGBoost underscores the powerful capabilities of ensemble learning methods like XGBoost, LightGBM, Gradient Boosting Classifier, and Hist Gradient Boosting Classifier in biomedical signal classification. To provide a clearer insight into the classifiers' performance, the following sections will present detailed results and graphs, as well as feature importance analyses for each model.

Table 2. XGBoost Confusion Matrix

True/Pred	0	1	2	3	4
0	9	0	1	1	0
1	0	18	0	3	2
2	3	3	21	1	1
3	2	0	1	11	0
4	1	0	1	0	21

Light GBM Performance:

Light GBM also performed well, achieving high accuracy and F1-score. Its memory-efficient design and histogram-based approach for identifying optimal splits made it particularly suitable for this classification challenge. While it performed admirably, its results were slightly less impressive compared to XG Boost.

Table 3. Light GBM Confusion Matrix

True \ Pred	0	1	2	3	4
0	10	0	1	0	0
1	1	19	0	1	2
2	3	3	21	1	1
3	2	0	1	11	0
4	1	0	2	0	21

Gradient Boosting Classifier Performance:

The Gradient Boosting Classifier showed good performance but proved to be computationally intensive and slow. While it performed well, its accuracy and F1-score were slightly lower than those of XGBoost and LightGBM, making it less ideal for large datasets or real-time applications.

Table 4. Gradient Boosting Confusion Matrix

True \ Pred	0	1	2	3	4
0	10	0	1	0	0
1	1	20	0	2	0
2	3	5	19	1	1
3	3	0	1	10	0
4	3	0	1	0	19

Hist Gradient Boosting Classifier Performance:

The Hist Gradient Boosting Classifier, an enhanced version of the Gradient Boosting Classifier, demonstrated excellent accuracy and F1-score, surpassing XGBoost. Its histogram-based approach enabled faster training and prediction times, making it an ideal choice for handling large datasets.

Table 5. Confusion matrix of Hist Gradient Boosting Classifier

True \ Pred	0	1	2	3	4
0	10	0	1	0	0
1	1	19	0	1	2
2	4	3	20	1	1
3	2	0	1	11	0
4	2	0	1	0	20

Stacking Classifier:

The Stacking Classifier combines the best models from the previous phase of training. It utilizes a meta-estimator, in this case, logistic regression, to aggregate the predictions from multiple base estimators.

Table 6. Stacking Classifier Confusion Matrix

True \ Pred	0	1	2	3	4
0	9	1	1	0	0
1	1	19	0	1	2
2	2	3	22	1	1
3	2	0	1	11	0
4	2	0	1	0	20

Discussion:

The experimental results demonstrate the effectiveness and ease of using machine learning classifiers for computerized wrist pulse diagnosis. XGBoost and Hist Gradient Boosting Classifier achieved the best performance, showing high accuracy and F1-scores. Feature importance analysis offered valuable insights into which aspects of the pulse signals were most indicative of specific health conditions. The results of this study demonstrate that machine learning models, particularly XGBoost and LightGBM, can effectively classify wrist pulse signals with promising accuracy. Our best-performing model achieved an accuracy of 83%, which indicates a strong potential for using pulse-based signals in health condition detection. These findings align with previous research efforts, such as those by researchers using pulse wave analysis in Traditional Chinese Medicine (TCM) studies, where similar machine learning techniques were employed for classification tasks with accuracies generally ranging between 80–90%. However, unlike traditional studies which often rely on handcrafted or rule-based features inspired by TCM, our approach was more data-driven and grounded in statistical and autocorrelation-based feature extraction.

In contrast to some earlier works that focused primarily on signal classification using neural networks or support vector machines (SVMs), our models XGBoost provided greater interpretability, faster training times, and competitive performance, especially in handling imbalanced datasets. Additionally, while other studies often use high-end pulse acquisition systems, our approach was built with the goal of being adaptable to low-cost, real-world applications, which could significantly improve accessibility in under-resourced healthcare settings. Another key distinction of our work lies in the emphasis on rolling statistical features, which are not commonly explored in existing studies. These features allowed our models to better understand the localized and temporal behavior of wrist pulses, providing a richer feature set for classification. Overall, the comparative performance of our models indicates that wrist pulse signals, when processed with effective statistical methods and machine learning algorithms, can offer a viable path toward non-invasive health monitoring solutions. Future studies can build on this foundation by exploring deep learning architectures and larger, more diverse datasets for broader generalizability. These results suggest that computerized/automated pulse diagnosis using machine learning can significantly enhance diagnostic accuracy and provide a standardized approach for analyzing pulse signals. This method has the potential to reduce the subjectivity inherent in traditional pulse diagnosis, helping clinicians make more informed decisions. Moreover, this approach offers a straightforward and side-effect-free method for diagnosing pulse-related health conditions. Below are the tables for different classifiers with their different accuracies and results.

Light GBM Results:

Accuracy: 80.00%

Table 7. LightGBM results output

Class	Precision	Recal	F1-score	Support
Normal	0.56	0.91	0.69	11
Acute appendicitis	0.86	0.83	0.84	23
Appendicitis	0.84	0.72	0.78	29
Diabetes	0.85	0.79	0.81	14
Pancreatitis	0.86	0.83	0.84	23
Accuracy			0.80	100
Macro Avg	0.79	0.81	0.79	100
Weighted Avg	0.82	0.80	0.80	100

XGBoost Results:

Accuracy: 83.00%

Table 8. XGBoost results output

Class	Precision	Recal	F1-score	Support
Normal	0.64	0.82	0.72	11
Acute appendicitis	0.87	0.87	0.87	23
Appendicitis	0.85	0.79	0.82	29
Diabetes	0.79	0.79	0.79	14
Pancreatitis	0.91	0.87	0.89	23
Accuracy			0.83	100
Macro Avg	0.81	0.83	0.82	100
Weighted Avg	0.84	0.83	0.83	100

Gradient Boosting Results:

Accuracy: 78.00%

Table 9. Gradient Boosting results output

Class	Precision	Recal	F1-score	Support
Normal	0.50	0.91	0.65	11
Acute appendicitis	0.80	0.87	0.83	23
Appendicitis	0.86	0.66	0.75	29
Diabetes	0.77	0.71	0.74	14
Pancreatitis	0.95	0.83	0.88	23
Accuracy			0.78	100
Macro Avg	0.78	0.79	0.77	100
Weighted Avg	0.82	0.78	0.79	100

Hist Gradient Boosting Results:

Accuracy: 81.00%

Table 10. Hist Gradient Boosting results output

Class	Precision	Recal	F1-score	Support
Normal	0.56	0.82	0.67	11
Acute appendicitis	0.83	0.83	0.83	23
Appendicitis	0.88	0.76	0.81	29
Diabetes	0.85	0.79	0.81	14
Pancreatitis	0.87	0.87	0.87	23

Accuracy			0.81	100
Macro Avg	0.80	0.81	0.80	100
Weighted Avg	0.83	0.81	0.81	100

Stacking Classifier Results:
Accuracy: 80.00%

Table 11. Stacking Classifier's results output

Class	Precision	Recal	F1-score	Support
Normal	0.53	0.91	0.67	11
Acute appendicitis	0.86	0.83	0.84	23
Appendicitis	0.87	0.69	0.77	29
Diabetes	0.85	0.79	0.81	14
Pancreatitis	0.87	0.87	0.87	23
Accuracy			0.80	100
Macro Avg	0.80	0.82	0.79	100
Weighted Avg	0.83	0.80	0.80	100

From the results above, it is clear that XGBoost and Hist Gradient Boosting Classifier showed the best performance on the given dataset, with accuracies of 83.00% and 81.00%, respectively.

Novelty:

This study presents a fresh perspective on health monitoring by focusing on the subtle signals carried in the human wrist pulse. While wrist pulse analysis has long been a part of traditional diagnostic systems, especially in Eastern medicine used in ancient practices like Traditional Chinese Medicine (TCM), it has rarely been explored with modern machine learning techniques in a scientific, data-driven way. Our project bridges this gap by combining classical pulse reading concepts with state-of-the-art algorithms like XGBoost and LightGBM, Gradient Boosting & Hist Gradient Boosting to identify patterns linked to specific health conditions. What sets this work apart is its focus on creating an accessible, non-invasive, and cost-effective tool that could be used even in low-resource settings. This approach not only supports early disease detection but also opens up new possibilities for integrating AI with physiological signals in practical healthcare applications.

Recommendations for Future Research:

- **Expansion of the Dataset:** To enhance the robustness and generalizability of the classifiers, expanding the dataset to include a larger and more diverse range of illnesses and medical conditions would be beneficial.
- **Adding Additional Physiological Signals:** Combining wrist pulse signals with other physiological data, such as blood pressure and ECG, would improve diagnostic accuracy and provide a more comprehensive evaluation of cardiovascular health.
- **Deep Learning:** Incorporating deep learning models, such as Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs), could help capture more complex patterns and relationships in the data, ultimately improving detection accuracy and precision.
- **Real-time Applications:** Developing a real-time computerized pulse diagnostic application could allow for practical deployment and offer insights into patient acceptability, ease of use, and integration with current healthcare systems.

Acknowledgement:
We sincerely thank all those who helped us in making this project a success, especially the faculty and staff at UET Peshawar, for their essential support and direction during this study.

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