



Unveiling Key Predictors for Early Heart Attack Detection using Machine Learning and XAI Technique using LIME

Prakash Paudel*
visitppdl@gmail.com
Nepal College of Information
Technology
Lalitpur, Bagmati, Nepal

Satish Kumar Karna*
satishkarna76@gmail.com
Nepal College of Information
Technology
Lalitpur, Bagmati, Nepal

Ruby Saud
mysticrubs94@gmail.com
Nepal College of Information
Technology
Lalitpur, Bagmati, Nepal

Loknath Regmi
lnregmi046@pcampus.edu.np
IOE, Pulchowk Campus
Lalitpur, Bagmati, Nepal

Tara Bahadur Thapa
email2tarathapa@gmail.com
Gandaki College of Engineering &
Science
Pokhara, Gandaki, Nepal

Mohan Bhandari†
mail2mohanbhandari@gmail.com
Samriddhi College
Bhaktapur, Bagmati, Nepal

ABSTRACT

The prominence of cardiovascular diseases, particularly heart attacks, as a leading cause of global mortality is highlighted, with an increasing number of deaths attributed to cardiovascular diseases over the years. Amidst these challenges, artificial intelligence (AI) and machine learning (ML) technologies emerge as powerful tools in healthcare. This study conducts a comparative analysis of predictive features extracted from diverse classification algorithms, including AdaBoost Classifier (ABC), Random Forest (RF), Gradient Boosting Classifier (GBC) and Light Gradient-Boosting Machine (LGBM), aiming to identify common patterns in predictive outcomes. LGBM emerges as the standout performer among classification algorithms, boasting a remarkable average training accuracy of 99.33%. Results demonstrate comparable precision, recall, and F1 scores among RF, GB, and LGBM, while ABC lags behind. The study reveals from eXplainable AI technique that consistent attribution of importance to attributes like "kcm" and "troponin" across all methods for classifying "Attack" instances, indicating their pivotal role in prediction. The research underscores the potential clinical application of machine learning for heart attack diagnosis and suggests the adoption of various deep learning techniques to enhance predictive performance.

CCS CONCEPTS

• ML Models with Heart Attack Dataset → Major contributing features for heart attack.

*Both authors contributed equally to this research.

†Corresponding Author



This work is licensed under a Creative Commons Attribution International 4.0 License.

NSysS 2023, December 21–23, 2023, Khulna, Bangladesh
© 2023 Copyright held by the owner/author(s).
ACM ISBN 979-8-4007-0878-7/23/12.
<https://doi.org/10.1145/3629188.3629193>

KEYWORDS

AdaBoost, Random Forest, Explainable AI, Gradient Boosting, Heart Attack, LIME, Machine Learning

ACM Reference Format:

Prakash Paudel, Satish Kumar Karna, Ruby Saud, Loknath Regmi, Tara Bahadur Thapa, and Mohan Bhandari. 2023. Unveiling Key Predictors for Early Heart Attack Detection using Machine Learning and XAI Technique using LIME. In *10th International Conference on Networking, Systems and Security (NSysS 2023)*, December 21–23, 2023, Khulna, Bangladesh. ACM, New York, NY, USA, 8 pages. <https://doi.org/10.1145/3629188.3629193>

1 INTRODUCTION

The heart, the main organ of the human body, supplies blood through the blood vessels of the circulatory system to transport blood, oxygen, and other materials to the different organs of the body [18]. When a coronary artery becomes partially or completely blocked due to plaque buildup or a blood clot, the blood flow to a section of the heart muscle is reduced or cut off. This can lead to damage or death of the heart muscle cells and eventually, a heart attack [20]. According to a recent estimate from the World Heart Federation, the number of deaths caused by cardiovascular disease (CVD) increased globally from 12.1 million in 1990 to 20.5 million in 2021 accounting the largest cause of death globally, with low- and middle-income nations accounting for 4/5 of all CVD fatalities [25]. On the other hand, in spite of geographical locations, heart diseases are due to many reasons such as age factors, smoking, stress, lifestyle, diabetes, and blood pressure [31].

Artificial intelligence (AI) and Machine Learning (ML) are cutting-edge technologies that have a major impact on healthcare and individualized clinical support [15]. The importance of these fields is growing as available data formats for medical persons make it challenging to derive information from those patterns and make decisions [9]. Not only ML algorithms, even deep learning neural networks are also playing a major role in heart disease prediction assisting in analyzing the large amount of data that is available to physicians, investigating diagnostic patterns, streamlining them, and integrating the patient's records to prevent errors [3]. It is well aware that to provide immediate assistance and avoid fatal outcomes, early diagnosis of future heart attacks is essential [27],

the current ML and DL approach are only statistical and considered black box resulting the complex behaviour of the models [17]. To overcome the black box approach of the AI models and make understandable interpretations, the study explores the Explainable AI (XAI) algorithm: Local Interpretable Model-Agnostic Explanations (LIME) serve as interpretable tools that provide transparency to machine learning predictions [30]. By simulating the behavior of the model close to a particular instance, LIME produces local explanations for specific predictions [26]. With a thorough understanding of the causes of heart attacks for a particular record sample given by the XAI algorithms, doctors may consider the results of this study for decision-making.

The objectives of the proposed study are:

- (1) To predict the Heart attack for a given sample and compare the performance of five different machine learning models: AdaBoost Classifier (ABC), Random Forest (RF), Gradient Boosting Classifier (GBC) and Light Gradient-Boosting Machine (LGBM).
- (2) To identify the main factors affecting their predictions using Explainable AI algorithms with LIME.

2 RELATED WORKS

2.1 Machine Learning Approach

R.Bharti et al. [5] studied different ML and DL algorithms to compare the results for UCI Machine Learning heart disease dataset and the result showed that the accuracy of the 80.3%, 83.31%, 84.86%, 83.29%, 82.33% and 71.4% for Random Forest (RF), Logistic Regression (LR), K Nearest Neighbor (KNN), Support Vector Machine (SVM), Decision Tree (DT) and XGBoost. S. Mohan et al.[22] proposed hybrid HRFLM approach of RF and Linear Method (LM) to find the accuracy of 88.4% in predicting heart disease. F.S. Alotaibi [2] proposed a comparative analysis of classification algorithms, where the DT algorithm achieved the highest accuracy of 93.19%, following closely was SVM, RF, Naive Bayes(NB), LR with an accuracy of 92.30%, 89.14%, 87.27% and 87.36% in a line. A. K. Gárate-Escamila et al. [12] proposed a hybrid approach combining a chi-square (CHI) with principal component analysis (PCA) and discovered that CHI-PCA with RF performed best among the classifiers, with 98.7% accuracy for Cleveland, 99.0% accuracy for Hungarian, and 99.4% accuracy for CH datasets. S. Archana et al.[29] performed the comparative study and found out k-NN excelled in identifying patterns with accuracy of 87%, closely followed by SVM with 83% along with DT achieved 79% accuracy, while LR yielded 78%.

T.Guleria et al. [14] studied and evaluated various machine learning algorithms including SVM, KNN, AdaBoost, bagged trees, LR, and Gaussian naive Bayes for heart disease classification where in-depth XAI techniques like feature selection, explainable weight initialization, normalization, and optimization were also explored. The SVM algorithm outperforms others with an 82.5% accuracy, 84.7% F-measure, 91.5% recall and AUC is 0.89 on heart disease datasets. S. Folorunso et al.[10] research involved applying seven different ML models, which included k-NN, eXtreme Gradient Boosting, Extra Trees, DT, LGBMight, SVM, and RF, to the heart disease dataset. Various evaluation metrics such as recall, precision, F1-Score, accuracy, ROC, and RPC were utilized to assess the models and findings indicate that the Extra Trees model outperformed the others, achieving

an 87% accuracy, 0.88 precision, 0.86 RPC, 0.87 recall, 0.94 ROC, and 0.935 F1-score. T.Obasi et al.[23] used an approach that merges RF, Bayesian Classification, and LR to construct a medical decision support system for forecasting heart ailments consisting dataset of 1990 instances and 18 risk determinants where the system attained considerable accuracy of RF at 92.44%, NB at 61.96%, and LR at 59.7% and these findings were validated using authentic medical records. MM. Rahman et al.[24] proposed a prediction system along with a user-friendly website for swift at-home heart condition assessment that has a sample size of 1026 that accurately detect heart disease based on thirteen health parameters, encompassing factors like age, gender, chest pain type, blood pressure, and ECG where they employed eight distinct algorithms—KNN, XgBoost, LR, SVM, Ada Boost, DT, NB, and RF. The result showed that DT and RF exhibit superior performance with an accuracy of DT 99%, RF 99%, XgBoost 95%, KNN 89%, SVM 85%, LR 85%, Ada Boost 83%, and NB 82%.

2.2 Deep Learning Approach

H. Kathleen et al.[21] implemented a deep neural network (DNN) to diagnose heart disease and achieved 83.67% accuracy, 93.51% sensitivity, and 72.86% specificity using clinical data from 303 patients which produce precision of 79.12% and F-Score of 0.8571. Also, the model's area under the ROC curve stood at 0.8922, indicating effective discrimination and the Kolmogorov-Smirnov test score obtained was 66.62%, while the diagnostic odds ratio was 38.65, with a 95% confidence interval. K. Saikumar et. al [28] carried out research involving deep learning categorization using DCAlexNet CNN. Heart disease specifics and the size of the affected areas were determined using trained features from a.csv file. The ensuing confusion matrix revealed noteworthy performance metrics including 98.67% accuracy, 97.45% sensitivity, 99.34% recall, and a 99.34% F1 Score. F. Ali et.al [1] presented a smart healthcare system that employs feature fusion and an ensemble deep learning model for cardiac disease prediction. Their system integrated sensor data and electronic medical records, applied feature selection to reduce computational load and utilized feature weighting to enhance accuracy rate of 98.5%.

3 METHODOLOGY

Fig. 1 displays the abstract architecture of the workflow composed of data preprocessing, different algorithms implemented, and statistical performance measures from the models and explanation frameworks.

For better accuracy, categorical data of 'Attack' and 'Normal' samples labeled as 'Positive' and 'Negative' are mapped into 1 and 0. After labeling, entire data samples are fitted into a standard scaler and imposed to individual algorithms: ABC, RF, GBC and LGBM. The statistical performance metrics were calculated and the model was further elaborated with XAI Algorithm i.e. LIME. Tabular explanation from LIME were used to determine the major contributing features to predict the particular instance as Attack or Normal.

3.1 Datasets

3.1.1 Description. In this study, publicly available Heart Attack Dataset [4] is used with 8 features namely 'age', 'gender', 'implyse', 'pressurehigh', 'pressurelow', 'glucose', 'kcm', 'troponin' and an

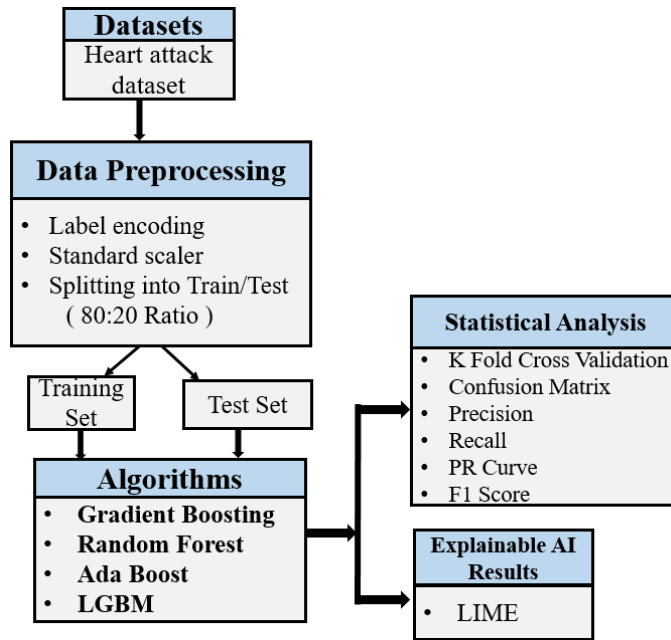


Figure 1: Methodology

Algorithm 1 Unveiling Key Predictors for Early Heart Attack Detection using Machine Learning and Explainable AI Technique using LIME

Require: Categorical Data(Break down in ratio 80:20) with size 1319 × 9

Algorithms Used: ABC, RF, GBC and LGBM

for For every sample data in individual algorithm **do**
 Calculate LIME values

end for

Calculate: Confusion Matix, Recall, Precision, F1 Score and PR Curve

Implement XAI: Impose ABC, RF, GBC and LGBM to LIME to generate explainable results

target class as 'Class' with 'Positive' and 'Negative' for Attack and Normal samples.

3.1.2 Feature Selection. The correlation values between feature pairs in the dataset's eight features, as shown in Figure 2 using Pearson's correlation coefficient, were consistently lower than 0.7 [8]. As a result, it was decided that all of these aspects should be incorporated into the model.

3.1.3 Data Pre-processing. To make the knowledge discovery process more accessible and qualified, incomplete, noisy, or inconsistent datasets are preprocessed before using categorization algorithms. Categorical field (Class) is mapped as target value and rest of the features are used as model attributes. The data is divided into train and test set in a 4:1 ratio i.e. Out of 1319 samples, 1055 samples were used as training sets where as 264 samples were used as test data.

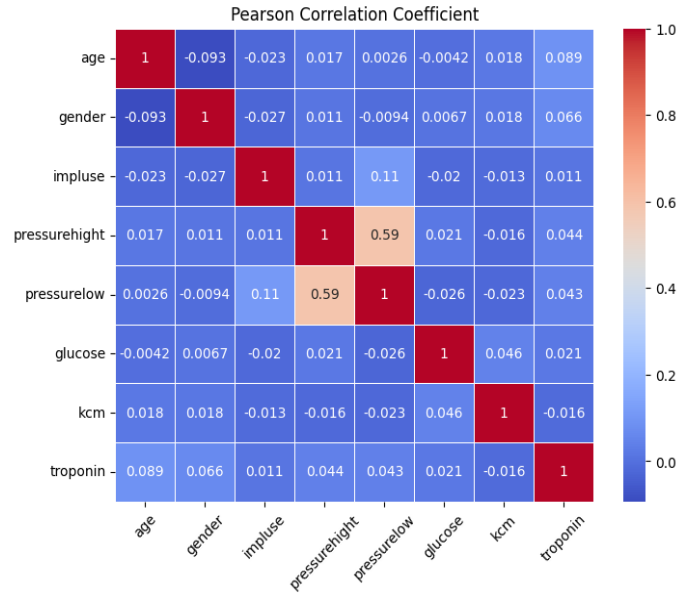


Figure 2: Pearson Correlation Coefficient

3.2 Algorithm Selection

The primary meanings for selecting the individual algorithms are listed as follow.

- (1) ABC successfully addresses imbalanced data and enhances classification performance by iteratively adjusting instance weights to improve the accuracy of weak learners [19]
- (2) Gradient Boosting Classifier is able to handle complicated data patterns and a variety of loss functions since it iteratively builds models to reduce loss gradients [11].
- (3) LightGBM's effective histogram-based technique and leaf-wise tree development reduce memory usage and training time [16].
- (4) Random Forest offers comprehensible frameworks that help with non-linear relationship management and feature importance analysis [6].

Due to their adaptability and predictive strength, these algorithms find use in a variety of industries [7].

3.3 LIME

LIME makes it possible to visualize every aspect for result analysis. LIME needs model-specific data to assess a model's local correctness[32]. Even though it might not be relevant to the overall model, local accuracy measures how well a model captures the characteristics surrounding a particular prediction.

LIME operates by selecting a target instance x , model f and generating perturbed instances x'_i in its vicinity. The model's predictions $f(x)$ and $f(x'_i)$ are obtained, and interpretable features z_i are extracted from the perturbed instances. All the interpretable ML models $g(z)$, were trained using pairs $(z_i, f(x'_i))$ to approximate the complex behavior of f in the local neighborhood of x . To analyse $g(z)$, coefficients β_i in $g(z)$, the importance of the corresponding

features z_i in influencing the predictions were reflected. Larger absolute values of β_i indicate stronger influences [13].

3.4 Evaluation Metrics and Experimental Setup

3.4.1 Evaluation Criteria. All algorithms implemented are evaluated according to the following standards: Confusion Matrix, Precision, Recall, F1-Score, PR Curve.

3.4.2 Environmental Setup. The ML model and XAI algorithms were developed with the use of Python. The experiments were conducted on Google Colab, utilizing an NVIDIA K80 GPU and 12 GB of RAM provided by Google. Specifically, the runtime environment in Google Colab used Python version 3.7, Keras version 2.5.0, and the TensorFlow version 2.5.0 framework.

4 RESULT ANALYSIS

4.1 AdaBoost Classifier

4.1.1 Confusion Matrix. Figure 3 shows that 7 normal samples were miss-classified as attacks whereas 3 attack samples were miss-classified as normal.

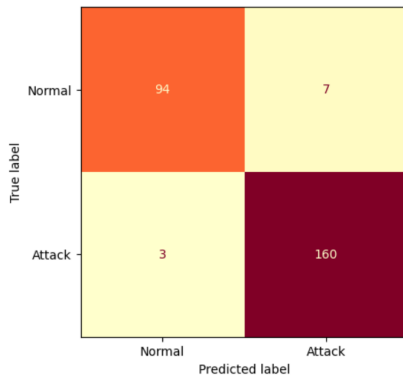


Figure 3: Confusion Matrix for AdaBoost

4.1.2 Classification Report. Table 1 was obtained as the classification report of AdaBoost where accuracy represents the overall correctness 96.21%. The macro-average metrics indicates a balanced performance with a precision of 0.96358, recall of 0.95614, and F1-score of 0.9596. The weighted-average metrics, considering the class distribution, yield a precision of 0.96229, recall of 0.96212, and F1-score of 0.96197.

Category / Metrics	Precision	Recall	F1-score	Support
Normal	0.96907	0.93069	0.94949	101
Attack	0.95808	0.9816	0.9697	163
accuracy			0.96212	264
macro avg	0.96358	0.95614	0.9596	264
weighted avg	0.96229	0.96212	0.96197	264

Table 1: Classification Report for AdaBoost

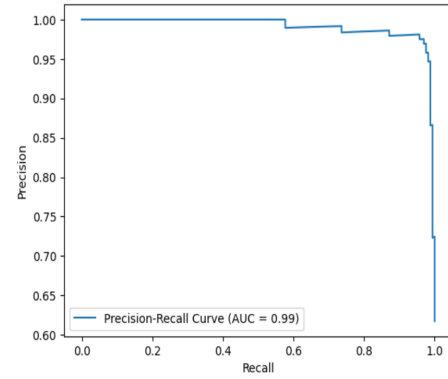


Figure 4: PR Curve for AdaBoost

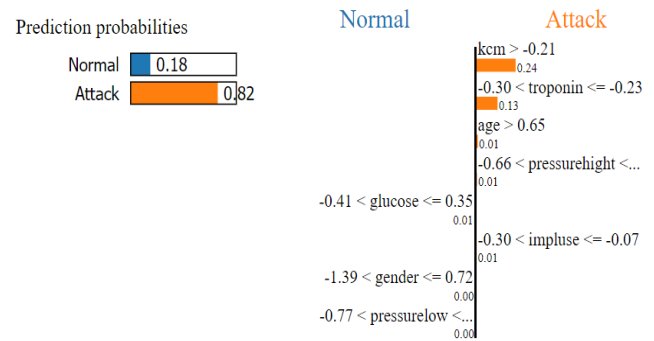


Figure 5: AdaBoost LIME Tabular Plots

4.1.3 PR Curve. Figure 4 shows the precision recall relation with AUC value of 99%.

4.1.4 LIME. Local interpretation of an instance (index 0) was imposed with LIME and ABC model which predicted the sample as **Attack** by 82% as shown in prediction probabilities in Figure 5. Features like kcm, troponin, age, pressureheight and impulse predict the instance as Attack by 24%, 13%, 1% and 1% respectively where as features like glucose, gender, and pressure played the negative role.

4.2 Random Forest

4.2.1 Confusion Matrix. Figure 6 shows that 2 normal samples were miss-classified as attack whereas 2 attack were miss-classified as normal.

4.2.2 Classification Report. Table 2 was obtained as the classification report of RF where Class 0 has a precision, recall, and F1-score of approximately 0.98020, with 101 instances. Class 1 exhibits similar values of about 0.98773 with 163 instances. The overall accuracy is around 0.98485. The macro-averaged and weighted-averaged values for precision, recall, and F1-score are approximately 0.98396 and 0.98485, respectively.

4.2.3 PR Curve. Figure 7 shows the precision recall relation with AUC value of 99%.

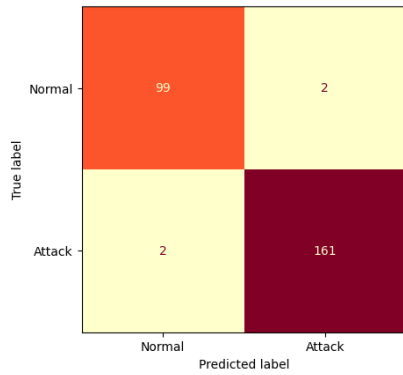


Figure 6: Confusion Matrix for RF

Category / Metrics	Precision	Recall	F1-score	Support
Normal	0.98020	0.98020	0.98020	101
Attack	0.98773	0.98773	0.98773	163
accuracy			0.98485	264
macro avg	0.98396	0.98396	0.98396	264
weighted avg	0.98485	0.98485	0.98485	264

Table 2: Classification Report for RF

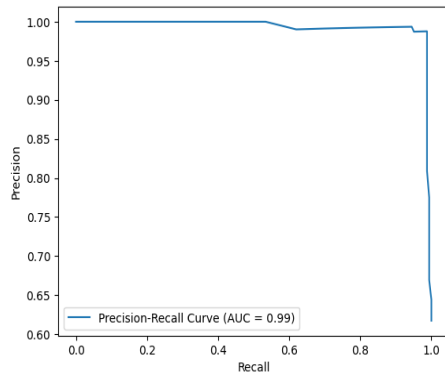


Figure 7: PR Curve for RF

4.2.4 *LIME*. Test record with index 0 is predicted as **Attack** by 100% and the features like troponin, kcm, troponin and age play 43%, 42% and 2% role respectively as shown in Fig.8.

4.3 Gradient Boost Classifier

4.3.1 *Confusion Matrix*. Figure 9 shows that 4 normal samples were miss-classified as attack whereas 2 attacks were miss-classified as normal.

4.3.2 *Classification Report*. Table 3 was obtained as the classification to show attack samples were predicted better than normal samples, showing a notably higher recall of 0.9877 versus 0.9604. The attack category achieves a higher F1-score of 0.9817 than Normal suggesting a better balance between precision and recall.

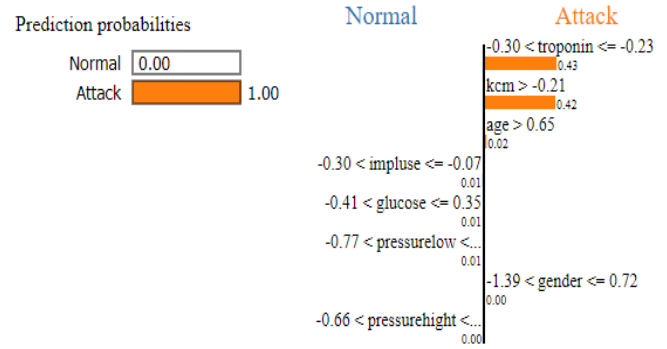


Figure 8: RF LIME Tabular Plots

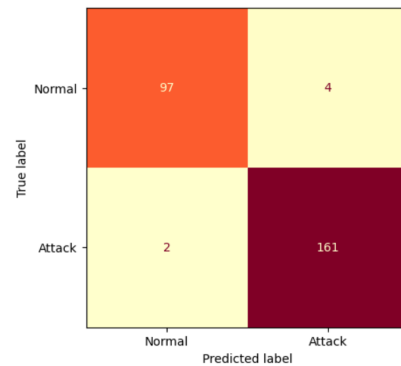


Figure 9: Confusion Matrix for GB

Category / Metrics	Precision	Recall	F1-score	Support
0	0.9798	0.9604	0.97	101
1	0.9757	0.9877	0.9817	163
accuracy			0.97727	264
macro avg	0.9778	0.974	0.9758	264
weighted avg	0.9773	0.9772	0.9772	264

Table 3: Classification Report for GB

4.3.3 *PR Curve*. Figure 10 shows the precision recall relation with AUC value of 99%.

4.3.4 *LIME*. Test record with index 0 is predicted as **Attack** by 100% whereas it is predicted as Normal by 0% as shown in prediction probabilities in Figure 11. Features like kcm, troponin, pressure height and age the instance as Attack by 48%, 48%, 2% and 1% respectively.

4.4 LGBM Classifier

4.4.1 *Confusion Matrix*. Figure 12 shows that 3 normal samples were miss-classified as attack whereas 2 attack were miss-classified as normal.

4.4.2 *Classification Report*. Table 4 was obtained to show that attack category out performed normal category in terms of prediction in different evaluation metrics like precision, recall and F1score.

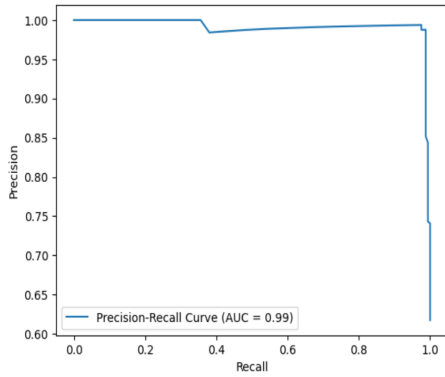


Figure 10: PR Curve for GB

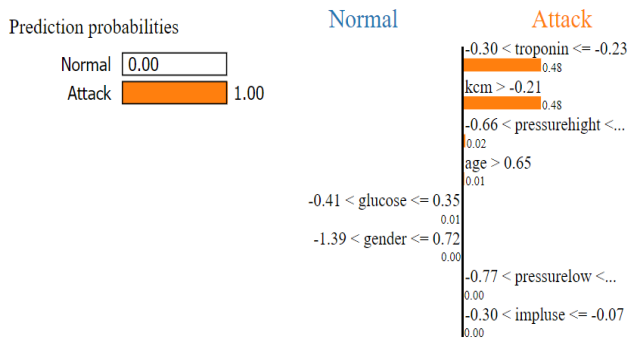


Figure 11: GB LIME Tabular Plots

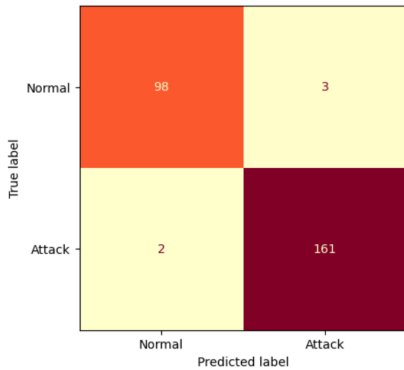


Figure 12: Confusion Matrix for LGBM

	Precision	Recall	F1-score	Support
0	0.9798	0.9604	0.97	101
1	0.9757	0.9877	0.9817	163
accuracy			0.97727	264
macro avg	0.9778	0.974	0.9758	264
weighted avg	0.9773	0.9772	0.9772	264

Table 4: Classification Report for LGBM

4.4.3 *PR Curve*. Figure 13 shows the precision recall relation with AUC value of 100%.

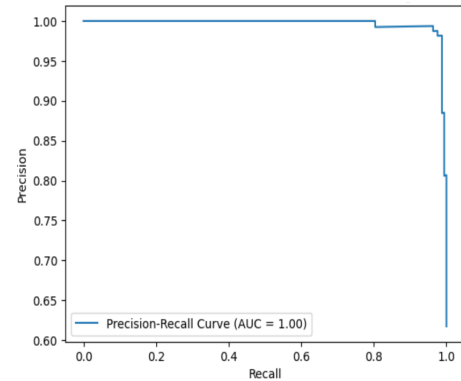


Figure 13: PR Curve for LGBM

4.4.4 *LIME*. Test record with index 0 is predicted as **Attack** by 100%. Figure 14 shows features like kcm, troponin, gender and glucose the instance as attack by 48%, 47%, 1% and 1% respectively.

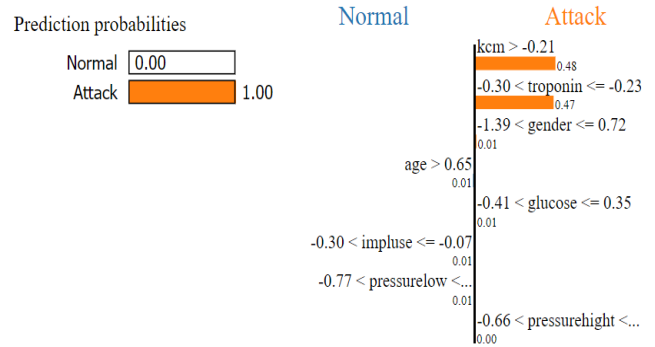


Figure 14: LGBM LIME Tabular Plots

5 COMPARATIVE ANALYSIS OF STATISTICAL RESULTS

Four Algorithms, ABC, RF, GB, and LGBM were implemented to predict whether the sample was Attacked or Normal. Table 5 shows the K-Fold cross-validation results and their average accuracy where the results show that LGBM (99.33%) slightly outperformed in training accuracy with other models. On comparative analysis of Four algorithms, ABC, RF, GB and LGBM in terms of their performance metrics for two categories: "Normal" and "Attack". RF, GB, and LGBM show approximately comparable precision, recall, and F1 scores across the four algorithms (F1-score: 0.97, precision around 97.03%, and recall as 96.04%). RF, GB, and LGBM algorithms consistently score well across both categories, while the ABC algorithm falls short slightly behind in all measurements.

Discussing the confusion matrix, ABC displayed the greatest misclassification rate, incorrectly labeling 10 instances. GB exhibited intermediate performance by misclassifying 6 instances each and

Table 5: Comparison of Training Accuracy with K fold cross validation

	Training Accuracy			
	ABC	RF	GB	LGBM
K1	100.00	100.00	99.00	100.00
K2	97.16	97.16	97.07	99.05
K3	96.22	98.11	98.1132	98.11
K4	99.05	99.05	99.05	99.05
K5	100.00	100.00	100.00	100.00
K6	96.19	96.19	97.14	97.14
K7	100.00	100.00	100.00	100.00
K8	100.00	100.00	100.00	100.00
K9	99.04	99.04	100.00	100.00
K10	100.00	100.00	100.00	100.00
Average	98.76	98.958	99.05	99.337

LGBM with instances misclassified, whereas RF demonstrated the highest performance, with only 4 instances misclassified highlighting its superior accuracy among the four algorithms.

Using the PR curve analysis for the four algorithms (ABC, RF, GB, and LGBM), it was observed that ABC, RF, and GB all achieved high PR values of 99, indicating strong performance in correctly classifying instances. LGBM outperformed them all with a perfect PR value of 100, suggesting the highest precision and recall combined.

6 COMPARATIVE ANALYSIS OF XAI LIME RESULTS

In order to find common trends in prediction, we carried out a thorough feature comparison across a number of machine-learning methods, including ABC, RF, GB, and LGBM. The results are shown in Table 7, where it can be seen that traits like "kcm" and "troponin" consistently emerged as important criteria for categorizing cases as "Attacks" across all these methods in our dataset. This study illustrates the robustness of these features across several algorithms, further highlighting their significance in the decision-making process while also offering insightful information about the crucial aspects of categorization. To completely comprehend the clinical significance of "kcm" and "troponin" in the context of heart attack diagnosis, additional research and domain-specific expertise will be necessary.

7 DISCUSSION

Several algorithms were evaluated on different heart disease datasets, and their performance varied in Table 6. For the UCI heart disease dataset, among the authors in [5] and [2], the highest accuracy was 93.19% for DT. Authors in [1] implemented Ensemble DL to get 98.5% for the Cleveland dataset whereas several other studies [22] and [21] also implemented the same dataset having lower accuracy. Though Several other studies also coped to get better accuracies, the proposed study achieved 99.33% accuracy using the LBGM algorithm along with the explainable algorithm LIME.

Table 6: Comparison table for different approaches with highest accuracy and dataset

Ref.	Algorithms Implemented	Highest Accuracy	XAI
[5]	RF, LR, KNN, SVM, DT, XGBoost Dataset: UCI Heart Disease	KNN: 84.86%	No
[22]	Hybrid RF with LM Dataset: UCI Cleveland	88.70%	No
[2]	DT, SVM, RF, NB, LR Dataset: UCI Heart Disease	DT: 93.19	No
[29]	KNN, SVM, DT, LR Dataset: UCI repository	KNN: 87%	No
[14]	SVM, KNN, LR, Gaussian NB, AdaBoost, BaggedTree, Dataset: Heart Disease	SVM: 82.5%	SHAP
[10]	Extra Tree, KNN, eXtreme GB, DT, LGBM, CVM, RF Dataset: Heart Disease	Extra Tree: 87%	No
[24]	DT, RF, XGBoost, NB, KNN, SVM, LR, AdaBoost Dataset: UCI Vascular heart disease	DT and RF: 99%	No
[21]	DNN Dataset: Cleveland clinic Foundation	83.67%	No
[28]	DCAlexNet CNN Dataset: ADNI dataset	98.67%	No
[1]	Ensemble DL Dataset: Cleveland	98.50%	No
	Proposed Dataset: Heart disease classification	LBGM: 99.33%	LIME

Table 7: LIME Comparative Analysis for Attack and Normal for ABC, RF, GB and LGBM

	Attack	Normal
ABC	kcm, troponin, age, impulse, pressureheight	glucose
RF	kcm, troponin, pressureheight	impulse, age
GB	kcm, troponin, pressure height, age	glucose
LGBM	kcm, troponin, gender, glucose	age, impulse

8 CONCLUSION AND IMPLICATIONS

The performance of four classification algorithms—ABC, RF, GB, and LGBM were experimented with, where LGBM emerged as the standout performer, achieving an impressive average training

accuracy of 99.33%. The results revealed that RF, GB, and LGBM demonstrated comparable precision, recall, and F1 scores, effectively discerning "Normal" instances with high precision and exhibiting robust recall for "Attack" cases. In contrast, ABC lagged in all measured aspects, exhibiting the highest misclassification rate. PR curve analysis underscored the overall strong classification capabilities of all algorithms, with LGBM particularly excelling with a PR value of 100. Also, examination of feature selection from XAI algorithms using LIME, it indicated that the significance of "troponin" and "kcm" was higher in predicting the sample as an attack.

Several ensemble and deep learning approaches with more generalized record samples can with the elaborated result from Explain Like I'm 5 (Eli5) and Shapley Additive exPlanations (SHAP) to generate the medical sensations.

ACKNOWLEDGMENTS

This research was jointly conducted by Nepal College of Information Technology, Research Cell in collaboration with Samriddhi College and supported by University Grant Commission (UGC), Nepal (Grants ID: CRG:078/79-Engg-01).

REFERENCES

- [1] Farman Ali, Shaker El-Sappagh, SM Riazul Islam, Daehan Kwak, Amjad Ali, Muhammad Imran, and Kyung-Sup Kwak. 2020. A smart healthcare monitoring system for heart disease prediction based on ensemble deep learning and feature fusion. *Information Fusion* 63 (2020), 208–222.
- [2] Fahd Saleh Alotaibi. 2019. Implementation of machine learning model to predict heart failure disease. *International Journal of Advanced Computer Science and Applications* 10, 6 (2019).
- [3] Filippo Amato, Alberto López, Eladia María Peña-Méndez, Petr Vaňhara, Aleš Hampl, and Josef Havel. 2013. Artificial neural networks in medical diagnosis. , 47–58 pages.
- [4] Bharath011. 2023. *Heart Disease Classification Dataset*. <https://www.kaggle.com/datasets/bharath011/heart-disease-classification-dataset> Accessed: 2023, august 10.
- [5] Rohit Bharti, Aditya Khamparia, Mohammad Shabaz, Gaurav Dhiman, Sagar Pande, and Parneet Singh. 2021. Prediction of heart disease using a combination of machine learning and deep learning. *Computational intelligence and neuroscience* 2021 (2021).
- [6] Gérard Biau and Erwan Scornet. 2016. A random forest guided tour. *Test* 25 (2016), 197–227.
- [7] Salah Bouktif, Ali Fiaz, Ali Ouni, and Mohamed Adel Serhani. 2018. Optimal deep learning lstm model for electric load forecasting using feature selection and genetic algorithm: Comparison with machine learning approaches. *Energies* 11, 7 (2018), 1636.
- [8] Mohamad Adam Bujang and Nurakmal Baharum. 2016. Sample size guideline for correlation analysis. *World* 3, 1 (2016), 37–46.
- [9] Arwinder Dhillon, Ashima Singh, and Vinod Kumar Bhalla. 2023. A Systematic Review on biomarker identification for cancer diagnosis and prognosis in multi-omics: from computational needs to machine learning and deep learning. *Archives of Computational Methods in Engineering* 30, 2 (2023), 917–949.
- [10] Sakinat Oluwabukonla Folorunso, Joseph Bamidele Awotunde, Emmanuel Abidemi Adeniyi, Kazeem Moses Abiodun, and Femi Emmanuel Ayo. 2021. Heart disease classification using machine learning models. In *International Conference on Informatics and Intelligent Applications*. Springer, 35–49.
- [11] Xin Gao, Fang Deng, and Xianghu Yue. 2020. Data augmentation in fault diagnosis based on the Wasserstein generative adversarial network with gradient penalty. *Neurocomputing* 396 (2020), 487–494.
- [12] Anna Karen Gárate-Escamila, Amir Hajjam El Hassani, and Emmanuel Andrés. 2020. Classification models for heart disease prediction using feature selection and PCA. *Informatics in Medicine Unlocked* 19 (2020), 100330.
- [13] Alex Gramegna and Paolo Giudici. 2021. SHAP and LIME: an evaluation of discriminative power in credit risk. *Frontiers in Artificial Intelligence* 4 (2021), 752558.
- [14] Pratiyush Guleria, Parvathaneni Naga Srinivasu, Shakeel Ahmed, Naif Almusal-lam, and Fawaz Khaled Alarfaj. 2022. XAI framework for cardiovascular disease prediction using classification techniques. *Electronics* 11, 24 (2022), 4086.
- [15] Mohd Javaid, Abid Haleem, Ravi Pratap Singh, Rajiv Suman, and Shanay Rab. 2022. Significance of machine learning in healthcare: Features, pillars and applications. *International Journal of Intelligent Networks* 3 (2022), 58–73.
- [16] Guolin Ke, Qi Meng, Thomas Finley, Taifeng Wang, Wei Chen, Weidong Ma, Qiwei Ye, and Tie-Yan Liu. 2017. Lightgbm: A highly efficient gradient boosting decision tree. *Advances in neural information processing systems* 30 (2017).
- [17] Nagendra Prasad Krishnam, Mohd Shaikhul Ashraf, Balaji Ramkumar Rajagopal, Prashant Vats, DSK Chakravarthy, and Shaik Mohammad Rafi. 2022. Analysis Of Current Trends, Advances And Challenges Of Machine Learning (ML) And Knowledge Extraction: From ML To Explainable AI. *Industry Qualifications The Institute of Administrative Management UK* 58 (2022), 54–62.
- [18] Machine Learning. 2017. Heart disease diagnosis and prediction using machine learning and data mining techniques: a review. *Advances in Computational Sciences and Technology* 10, 7 (2017), 2137–2159.
- [19] Wonji Lee, Chi-Hyuck Jun, and Jong-Seok Lee. 2017. Instance categorization by support vector machines to adjust weights in AdaBoost for imbalanced data classification. *Information Sciences* 381 (2017), 92–103.
- [20] Peter Libby. 2006. Inflammation and cardiovascular disease mechanisms. *The American journal of clinical nutrition* 83, 2 (2006), 456S–460S.
- [21] Kathleen H Miao and Julia H Miao. 2018. Coronary heart disease diagnosis using deep neural networks. *international journal of advanced computer science and applications* 9, 10 (2018).
- [22] Senthilkumar Mohan, Chandrasegar Thirumalai, and Gautam Srivastava. 2019. Effective heart disease prediction using hybrid machine learning techniques. *IEEE access* 7 (2019), 81542–81554.
- [23] Thankgod Obasi and M Omair Shafiq. 2019. Towards comparing and using Machine Learning techniques for detecting and predicting Heart Attack and Diseases. In *2019 IEEE international conference on big data (big data)*. IEEE, 2393–2402.
- [24] Md Mahbubur Rahman. 2022. A web-based heart disease prediction system using machine learning algorithms. *Network Biology* 12, 2 (2022), 64.
- [25] World Heart Report. 2023. *DEATHS FROM CARDIOVASCULAR DISEASE SURGED 60% GLOBALLY OVER THE LAST 30 YEARS: REPORT*. <https://world-heart-federation.org/wp-content/uploads/World-Heart-Report-2023.pdf>
- [26] Marco Tulio Ribeiro, Sameer Singh, and Carlos Guestrin. 2018. Anchors: High-precision model-agnostic explanations. In *Proceedings of the AAAI conference on artificial intelligence*, Vol. 32.
- [27] Saima Safdar, Saad Zafar, Nadeem Zafar, and Naurin Farooq Khan. 2018. Machine learning based decision support systems (DSS) for heart disease diagnosis: a review. *Artificial Intelligence Review* 50 (2018), 597–623.
- [28] Kayam Saikumar, Vullanki Rajesh, and Bulepe Sankara Babu. 2022. Heart disease detection based on feature fusion technique with augmented classification using deep learning technology. *Traitement du Signal* 39, 1 (2022), 31.
- [29] Archana Singh and Rakesh Kumar. 2020. Heart disease prediction using machine learning algorithms. In *2020 international conference on electrical and electronics engineering (ICE3)*. IEEE, 452–457.
- [30] Gregor Stiglic, Primož Kocbek, Nino Fijacko, Marinka Zitnik, Katrien Verbert, and Leona Cilar. 2020. Interpretability of machine learning-based prediction models in healthcare. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery* 10, 5 (2020), e1379.
- [31] K Vembandasamy, R Sasipriya, and E Deepa. 2015. Heart diseases detection using Naive Bayes algorithm. *International Journal of Innovative Science, Engineering & Technology* 2, 9 (2015), 441–444.
- [32] Giorgio Visani, Enrico Bagli, Federico Chesani, Alessandro Poluzzi, and Davide Capuzzo. 2022. Statistical stability indices for LIME: Obtaining reliable explanations for machine learning models. *Journal of the Operational Research Society* 73, 1 (2022), 91–101.

Received 22 August 2023; revised 13 October 2023; accepted 25 October 2023