Spectrum of Engineering Sciences
ISSN (e) 3007-3138 (p) 3007-312X Volume 3, Issue 4, 2025

EARLY HEART ATTACK PREDICTION BY USING MACHINE LEARNING

Sarang Ali*[1], Abuzar Shahid[2], Gohar Mumtaz[3]

*[1,2,3]*Faculty of Computer Science and Information Technology, The Superior University, Lahore*

*[1]sarangalijrw@gmail.com, [2]abuzarbhutta@gmail.com, [3]gohr.m@superior.edu.pk

DOI: https://doi.org/10.5281/zenodo.15165379

Keywords
Machine learning, Light GBM classifier, Parameter tuning

Article History
Received on 17 February 2025
Accepted on 28 March 2025
Published on 07 April 2025

Corresponding Author: *

Abstract
Machine learning has been applied in different fields of life it is tremendously excelling in every field of life, exploring the secrets of life, enhancing the way of living, predicting new trends and trajectories, and paving the way for a new and advanced global home. ML is also a main contributor to the digital healthcare system. By using ML models healthcare professionals have been diagnosing different health issues and by using this leverage, we have been using ML models to predict the early threat of heart attack to support the healthcare system as well as human well-being. Heart Attack is one of the growing death concerns for Homo sapiens. Many people die every day owing to cardiac attacks which lead to devastating consequences. It often goes undetected until a critical event occurs, highlighting a pressing need for early and accurate risk assessment. This study aims to recognize entities at high jeopardy of cardiac events with an exceptional degree of accuracy. Prominently, the system is planned to alert users—encouraging them to consult with senior doctors promptly. For this study, we have used a publicly available secondary "Heart Attack Prediction" data set. For the training of the model of ML, we have torn apart the data set into a training set and a testing set with ratios of 90% and 10% respectively. For parameter fine-tuning, we used Python's Optuna library for the best ML model and its parameters. We found that the Light GBM classifier is best for binary classification and it shows promising benchmarks on test data.

INTRODUCTION

Nowadays, among the primary causes of mortality internationally is heart malady. It can be difficult to diagnose on time due to its confusing symptoms with other diseases. Treatment for it can be made extremely difficult by its intricacy, particularly if diagnosis is delayed. It encompasses a variety of conditions that make it difficult to identify its symptoms. These symptoms can be diagnosed wrong and aggravate the patient's health by putting their lives in danger. Heart disease is a result of various factors, which include elevated blood pressure, unhygienic and unhealthy diet, junk food, processed food, smoking, and other types of addiction, depression, and inactive lifestyles. It can be diagnosed with the help of different tests which include blood tests, angiograms (examination of arteries of the heart), X-rays, electro and echocardiograms, and muscular and pumping conditions through catheterization, check the working of valves (make sure of no blockage), stent placements, and cardiac tissue biopsies[1]. Almost all diagnostic procedures are costly, laborious, and inefficient for doctors and patients. A few years back, a huge rise in heart attacks was Observed specifically among youngsters. It happens either due to depression, unemployment, financial issues, limited access to diagnostic resources, costly treatment, and less availability of advanced solutions.

There is a dire need for computerized diagnostic systems to predict heart disease early (by analyzing pre-diabetes symptoms), accurately, quickly, and effectively instead of traditional methods. Any medical device that can identify this disease early, and prevent significant harm in terms of financial and, more crucially, human life savings. The link between heart disorders and patient's health conditions has been found through the use of numerous computational technologies and statistical techniques. They can lessen the likelihood that a patient will die from a heart attack by helping to forecast the possible risk of heart malady depending on the patient's underlying physical state beforehand. The reputation of predicting specific diseases through data mining and ML tactics has increased. Its focus is to use several ML algorithms to calculate cardiac disease. However, the traditional treatments are time-consuming, expensive, and unpleasant for both patients and medical staff. There is also no guarantee that they will predict the exact type of disease.

Automated technologies are beginning to appear as viable solutions. With their ability to detect the risk of heart disease more quickly and effectively than other traditional methods, By improving early recognition and diagnosis machine learning may be able to more effectively address the problems associated with cardiac disease [2]. Huge amounts of patients, diseases, and diagnostic data are generated daily. However, these data are not being utilized effectively to enhance patient outcomes. WHO published an annual report in 2019, that more than 17.9 million deaths are due to cardiac arrest or cardiac failure [3], and become the leading contributor to death. The data often go unanalyzed, missing opportunities to impact patient health positively. Targeting behavioral and environmental risk factors, such as smoking, eating poorly, being obese, not exercising, abusing alcohol, and being around pollution, can help prevent the majority of heart diseases. Preliminary detection of heart failure and the start of treatment with counseling and medication are crucial.

To diagnose heart failure early and start initial treatment with counseling and medications as soon as possible. It is crucial to address behavioral and environmental risk factors, which include smoking, poor diet, overweightness, lack of physical activity, other types of addiction, air pollution, family history, and lipid profile. Heart attacks and strokes cause 70% of heart deaths. 75% of people died due to heart attacks under

The age of 70 years. Most patients experience shortness of breath, and arm, shoulder, and chest pain. The most common sign that the cardiovascular system fails to pump enough blood is chest pain, and it has been for a long time. In medicine, this kind of cardiac discomfort is known as angina. To diagnose the issue, some tests such as MRIs, angiographies, and X-rays may be helpful.

In Pakistan, heart attack stands as a major health fear. This study aims to boost the accuracy of cardiovascular attack predictions using ML. The objective is to create trustworthy models that evaluate a person's risk for heart attack. These models will enable early detection and individualized care, thereby decreasing the side effects of heart attack on public health. The Statistics of the USA are in below table.

Table 1.

Topic	Statistics
Heart Disease Leading Cause of Death	Leading cause of mortality for the majority of racial and ethnic groupings, as well as for men and women.
Death Rate from Heart Disease	One person dies every 33 seconds from cardiovascular disease.
Total Heart Disease Deaths (2022)	In 2022, heart disease

	claimed the lives of 702,880 persons (1 in 5 fatalities).
Economic Cost (2019-2020)	The total cost of heart disease, including medical treatment, medications, and lost productivity, was around $252.2 billion.
Prevalence of Coronary artery disease (CAD)	About one in twenty adults age 20+ (5%) have CAD.
Deaths from CVD under Age 65 (2022)	Adults under 65 accounted for almost 1 in 5 cardiovascular disease-related fatalities.
Heart Attacks in the USA	Every forty seconds, a person has a heart attack.
Annual Heart Attacks in the USA	Every year, 805,000 people experience a heart attack (200,000 repeat victims, 605,000 first-time victims).
Attacks of the Heart that Are Silent	One in five heart attacks is silent; the victim remains unaware that harm has occurred.

The remaining paper is organized: The "literature review" section highlights relevant literature, while the "proposed methodology" section details the methodological framework. The "experimental results and discussion" section analyzes the study's findings, the "conclusion" provides final remarks and the last segment illustrates the conflict of interest.

Literature Review

Machine-learning technology has been extensively used for certain diagnostic issues and is especially well-suited for medical data analysis [4]. LR and SDG were utilized in a non-invasive method for forecasting heart illness in 303 patient files from the UPI repository. LR's accuracy was 91.67%, while SDG's was 80.0%. Machine learning and image fusion classification techniques are more accurate at predicting cardiac problems.[5]. The Random Forest (RF) approach obtained 93.8% accuracy after being tested for five distinct classifiers on 1670 datasets from exclusive hospitals in south India. [6]. The Boruta method is used to choose important characteristics following preprocessing, and Random Forest earned the greatest accuracy of 83.53% in a performance evaluation of the supervised ML algorithms for heart disease forecast on the Kaggle dataset. By using the grid CV approach and randomized CV, hyperparameter tuning was established for logistic regression feature reduction. The results were compared using seven distinct algorithm combinations. 100% accuracy was attained by combining Grid-Search and Linear Regression with the ensemble Kernal PCA methodology, where power transformation was used for preprocessing, and feature selection and a further tree classifier were used. [7]. Using logistic regression on the UCI dataset, heart disease was predicted; the model's accuracy was good, at around 87.10% for a 90:10 training-to-testing ratio.[8]. Three distinct datasets were subjected to an ensemble network, such as Linear Regression (LR), KNN, RF, XGBoost, and collective classifiers were tested for use in predicting heart disease; XGBoost attained an accuracy of 91%.[9.] Using data from the city of Cleveland, an attempt was made to forecast the risk of cardiovascular heart disease utilizing ML and DL.
A model trained using SVM, KNN, DT, RF and ANN analyzed their result after data preprocessing where the Artificial Neural network obtained better accuracy.[10]. By extracting decision rules, the CART

model, which stands for classification and regression tree was able to predict heart disease with 87% accuracy. [11]. Following data preprocessing and discretization on the UCI dataset, a feature selection approach known as minimal redundancy and maximum relevance was employed. Prediction algorithms like LR, DT LG-SVM, Naïve Bayes, and RF were utilized, with SVM achieving an accuracy of 84.85%. [12].

ML classifier approaches, such as LG, KNN, and RF, were exploit by using five various datasets of differenet EU cities. Among the three classifiers, RF and LG both achieved an accuracy of 88% [13]. The algorithms examine and group unlabeled datasets. Without human assistance, this learning will uncover the underlying patterns. Clustering approaches for heart disease prediction have been published. A classification and clustering system was created to forecast the heart dataset. The suggested model uses K-means clustering, in which functions are grouped using the Euclidian distance formula, and the data is preprocessed using normalization. High cholesterol and borderline cholesterol are two attribute values that are classified using logistic regression. Without normalization, the model's accuracy was 70.58%; with normalization, it was 84.84%; and with categorization, it was 90% accurate.

[14] . Using the city of Cleveland dataset, an integrated decision-making system was developed to forecast cardiac disease. The system employed random forest for classification, agglomerative for clustering, and Reduced dimensionality by exploiting PCA. When compared to other classifiers, the system's accuracy of 95.65% is superior. [15]. An attempt was made to predict heart illness utilizing PCA and HGA employing k-means on 303 medical datasets from the UPI repository. The hybrid k-means algorithm is utilized to cluster the data, and PCA is utilized to decrease characteristics. PCA is used to separate the dataset into PC1 and PC2 based on key properties. HGA is used to enhance clustering quality and decrease fitness. To enhance the quality of clustering, the steady state method is employed. The accuracy of the suggested approach was 94.06%. [16]. One study uses the UCI dataset to predict cardiac disease using a clustered genetic optimization technique. The k-means method is used to segment the data, and genetic optimization is used to classify the results. The benchmark of the suggested model was 94.56% when compared to basic classifiers such as DT, SVM, KNN Naïve Bayes, and others. Using a di-stage semi-supervised clustering approach, risk prediction for diabetes and cardiovascular disease was developed while taking biomarkers into account. After eliminating outliers, for this study, information from the US Centers for Disease Control and Prevention (CDC) and the National Health and Nutrition Examination Survey was used.

Approximately 7508 data points were used for the analysis of cardiovascular disease and 5389 data points for diabetes. The data is separated into two categories using semi-supervised K-means clustering: low-risk individuals and high-risk individuals who are at risk of developing an illness in the future. [17]. By exploiting ML and transfer learning to choose the right features for training and validation dataset to improve benchmarks, a technique for classifying and predicting heart disease was created. To determine the support values, the first step in data preparation is to lower the dimensionality and apply the margin rate conjugant scaling factor. The MLP neural network is utilized to train the model, while disease impact rate and relative feature margin selection are used to choose the labeled data. With a greater influence, the model forecasts the cardiac deficit rate. For both prediction and accuracy, the model's accuracy is contrasted with base classifiers.

Predicting cardiac attacks through utilizing big data analysis in healthcare is the target of this project. For 200 records, the model's classification accuracy was 96%, while its prediction accuracy was 82%. [18]. Using reinforcement learning (RL), a model was created to forecast cardiac illness. The Cleveland secondary dataset, which holds 303 records and employs the Q-learning basis of reinforcement learning (RL) for forecasting, is used to train the model. Only three factors—treetops, chol, and age—were employed in the development of the off-premised RL model, which then tells the agent to choose the optimal rules for the parameters. KNN and DT are utile to assess the recommended methods. The model beat KNN and DT with an accuracy of 0.8798.[19].

The table provides a synopsis of the conversion above.

Table 2.

Author	Results
(Okay)Miranda et al. [5]	Linear Regression: 91.67% Stochastic Gradient Descent: 80.0%
Maini, E.,[6]	Random Forest: 93.8%
Sujatha et al. [7]	Linear Regression: 80.22%
Ambesange et al. [8]	Linear Regression:90.32%
Rindhe, B [9]	Artificial neural network: 84.4% SVM:84.0%
Gangadhar et al. [10]	RF Classifier: 81.67%
Ozcan et al. [11]	Classification And Regressio Tree: 87%
Bashir et al. [12]	LG SVM: 84.85%
Patidar et al. [13]	Linear Regression:88% Random Forest: 88%
(Okay)Singh et al. [14]	Logistic Regression: 90%
Pati et al. [15]	IDMS: 95.65%
Okay Islam et al. [16]	Clustering: 94.06%
Vijaya [17]	Naïve Bayes: 88.52%
Sivaprasad et al. [18]	RFMS-MLPNN:82%
(OKAY)Prasanna et al. [19]	Ql earning: 0.8798

Methodology:

Dataset Details

For the initial prediction of heart attacks, we obtained a secondary dataset from the Kaggle. This dataset consists of binary classification: heart attack = “Yes” or heart attack = “No”. The dataset comprises 34 columns, covering general observations critical for heart attack prediction, such as:

Health Conditions: 'Sex', 'GeneralHealth', 'RaceEthnicityCategory', 'AgeCategory'

Lifestyle and Activities: 'PhysicalActivities', 'SmokerStatus', 'AlcoholDrinkers', 'ECigaretteUsage'

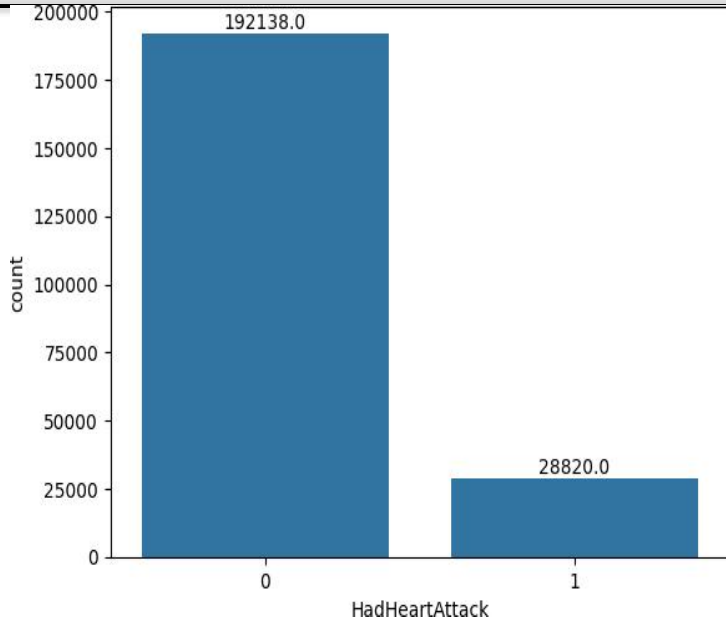
Medical History: 'HadHeartAttack', 'HadAngina', 'HadStroke', 'HadAsthma', 'HadSkinCancer', 'HadCOPD', 'HadDepressiveDisorder', 'HadKidneyDisease', 'HadArthritis', 'HadDiabetes'

Disabilities: 'DeafOrHardOfHearing', 'BlindOrVisionDifficulty',

Other Observations: 'LastCheckupTime', 'ChestScan', 'CovidPos', etc.

Of the 246,022 entries in the dataset, 10,576 are marked as "Yes" (heart attack) and 235,437 as "No" (no heart attack).

Revealed 33,797 outliers across multiple columns. After removing these outliers, the dataset was reduced to 212,216 records, with 202,562 labeled as 'No' and 9,654 as 'Yes'. The dataset is highly unbalanced, with the number of “yes” classes scarce. To escalate the number of “yes” classes, we used the SMOTE technique that enhanced the yes class to 28820. This data-scrubbing process ensures better accuracy in machine-learning models and enhances prediction reliability. By systematically addressing data anomalies, the dataset provides a robust foundation for building predictive models for early heart attack detection.



Training Dataset

The training dataset is instrumental in constructing and fine-tuning the predictive model. It enables the model to discern intricate patterns and establish meaningful relationships within the data. Through iterative learning, the model progressively adapts to optimize its prediction.

Testing Dataset

Conversely, the testing dataset functions as an independent benchmark. By exposing the model to unseen data, it rigorously evaluates its generalization ability, ensuring that the model performs effectively on real-world inputs and does not over-fit the training data.

Data Distribution

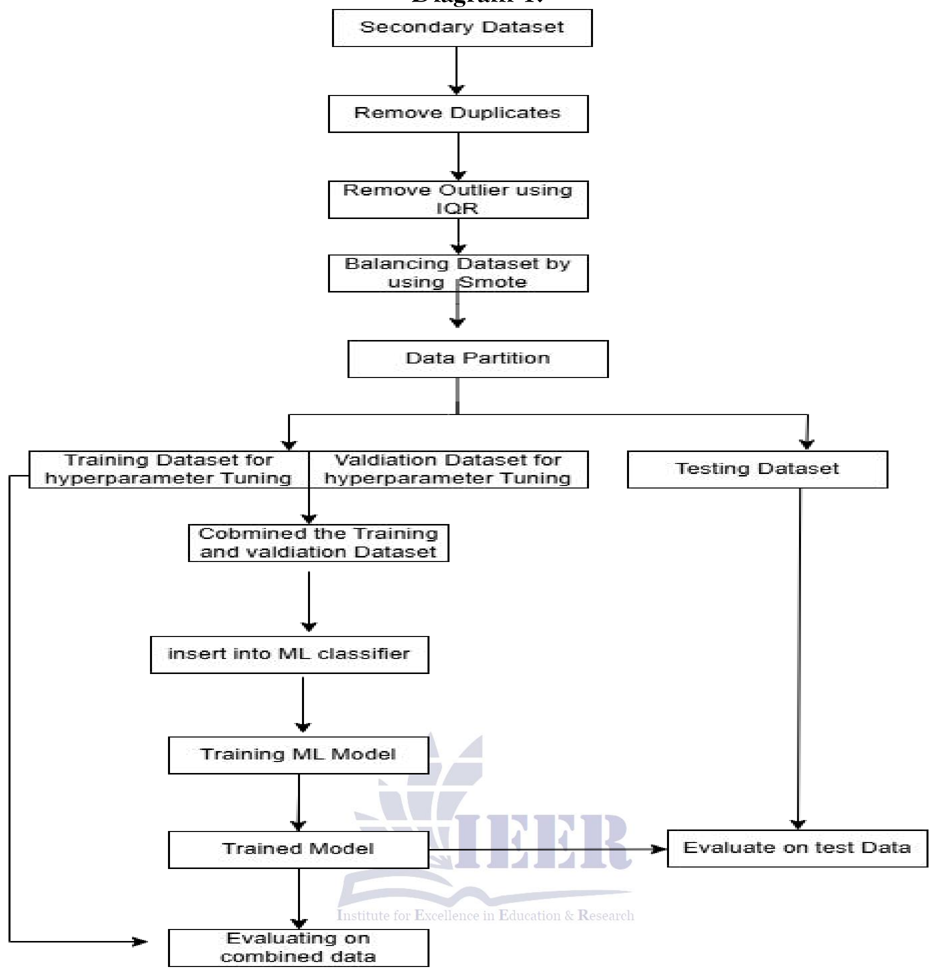
This 90:10 split strikes a balance between maximizing the data available for model static training and retaining sufficient data for evaluation. It is particularly advantageous for larger datasets, as it allows the model to pick up the conceal patterns from a comprehensive dataset while preserving the integrity of the evaluation process, resulting in reliable and actionable insights.

Hyperparameter Tuning:

As described in the data set a description that our data set is highly unbalanced and for the best aftermath. For that specific reason, there is highly likely to occur under-fitting problems. To mitigate that issue, we have utilized the hyperparameter tuning. Hyper-parameter tuning is the process of tuning the parameter to get more accurate and specific results. Hyper-parameters are parameters other than model parameters. There are many techniques over there to tune the parameters however, we have considered OPTUNA LIBRARY along with the TPE (Tree-Structured Parzen Estimator)[22] technique, which is known for its forecasting in optimizing hyperparameters. The results of the TPE sampler have been systematically over 333 trials. The TPE proved its efficiency in predicting outstanding hyperparameter values. The below diagram shows the summary of the Methodology.

Spectrum of Engineering Sciences
ISSN (e) 3007-3138 (p) 3007-312X Volume 3, Issue 4, 2025

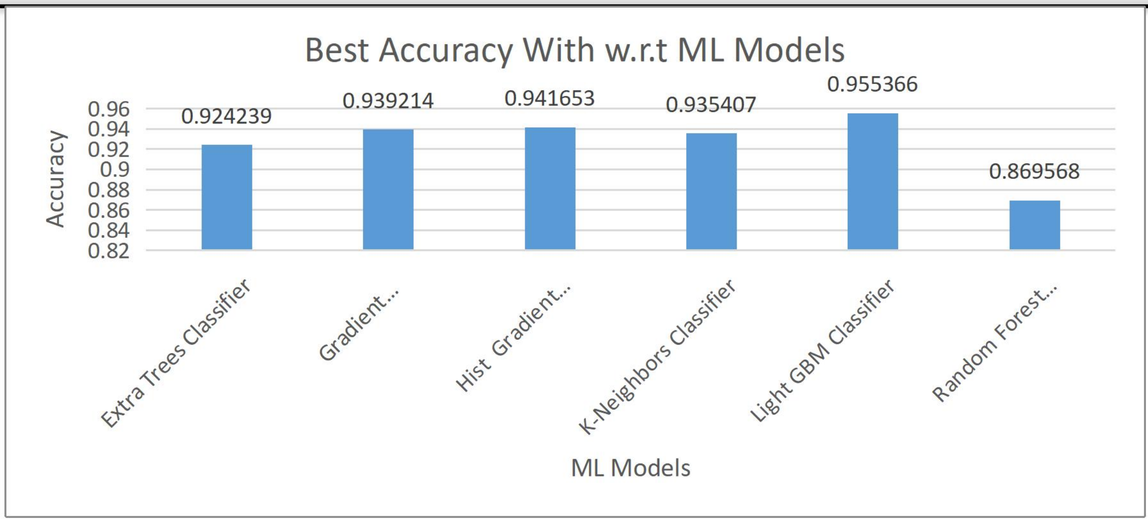
Diagram 1.



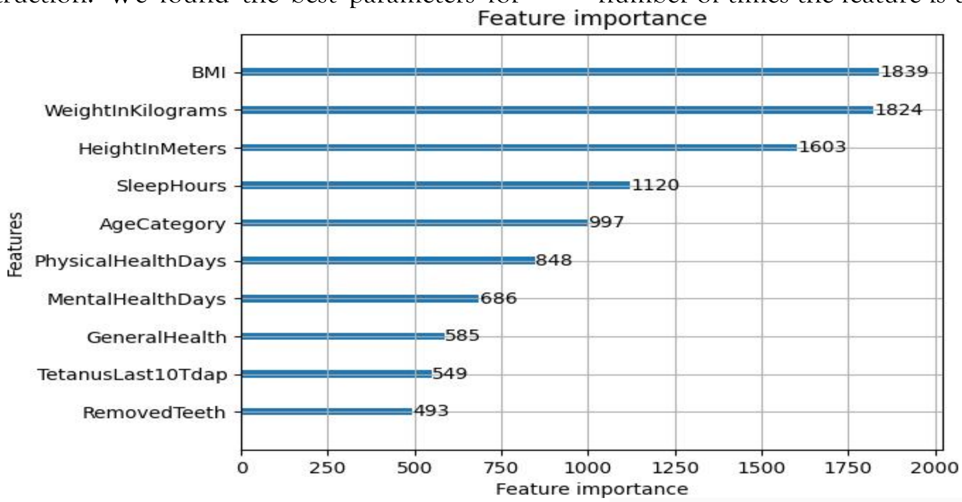
Classification:
For the prediction of heart attack, we utilized (6) six different classifiers and we have compared their performance results to figure out the best-performing model/ classifier for our data set. During this comparison, we have analyzed the results and we have found the GMB classifier the best performer among all of them. These are 6 models we have compared.

STATS
Table 3.

Models	AVG	Median	AVG (Standard Deviation)	Best max accuracy w.r.t
Extra-Trees Classifier	0.901278	0.897577	0.019302	0.924239
Gradient Boosting Classifier	0.883943	0.869568	0.022724	0.939214
Hist- Gradient Boosting Classifier	0.927532	0.934045	0.013064	0.941653
K-Neighbors Classifier	0.915736	0.911645	0.015100	0.935407
Light GBM Classifier	0.953931	0.954810	0.005519	0.955366
Random-Forest Classifier	0.869568	0.869568	0.000000	0.869568



After analyzing these results, we have figured out that the Light GMB Classifier performed best among all these classifiers. It is an ensemble technique that works on the basic gradient-boosting algorithm and also engages histogram-based algorithms for proficiency in tree construction. We found the best parameters for the LGMB classifier n_estimator =513, max_depths=39, boosting_type=Gradient Boosting Decision Tree, learning_rate= 0.1694, min_child_samples =20, reg_lambda= 0.8958. The most important feature on the basics of contains number of times the feature is used in the model.



Result and Discussion:

After mining of best parameters, we inserted these parameters into the Light GBM classifier Model, we trained the model on the entire training data. After training the model, we evaluate the model by using the test dataset. The ML model exhibits promising results on the test datatset as shown in the below table.

Classification report on testing data.

Table 4.

	Precision	Recall	F1 Score	Support
No Class	0.96	0.99	0.98	1921
Yes Class	0.92	0.74	0.82	2882
Accuracy			0.96	2209
Macro average	0.94	0.87	0.90	2209
Weighted average	0.96	0.96	0.96	220

				96

Confusion Matrix on Test Data
Table 5.

No Class	19018	2137
Yes Class	745	196
	No Class	Yes Class

Classification Report on Training Data:
Table 6.

	Precision	Recall	F1 Score	Support
No Class	0.97	1.00	0.98	172924
Yes Class	0.97	0.80	0.88	25938
Accuracy			0.96	198862
Macro average		0.90	0.93	198862
Weighted average		0.97	0.97	198862

Confusion Matrix on Train Data.
Table 7.

No Class	172371	553
Yes Class	5160	20778
	No Class	Yes Class

Conclusion
Thousands of people pass away each year owing to sudden heart attacks and other diseases that cause heart attacks, this study helps to mitigate the death rate due to heart attack because it predicts the heart attack it prediction is "yes". The patient could contact with cardiologist for treatment early indicators help to save human lives. But as we know it's an ML model, and it could also make errors in predictions.

Conflict of interest:
Trained LGMB Classifier ML algorithm most likely to best perform on Americans. Because the model is trained on the USA base dataset. Therefore, we are not concerned about the other demographic locations.

REFERENCES
Alalwan, A. A. (2018). Investigating the impact of social media advertising features on customer purchase intention. *International Journal of Information Management, 42*, 65-77.
Alhabash, S., Mundel, J., & Hussain, S. A. (2017). Social media advertising: Unraveling the mystery box. In *Digital advertising* (pp. 285-299): Routledge.
Antoniadis, I., Assimakopoulos, C., & Paltsoglou, S. (2021). Engagement and reactions of brand posts on brand fan pages in Facebook: an investigation of brand posts' characteristics. *International Journal of Internet Marketing and Advertising, 15*(4), 352-367.
Arya, V., Paul, J., & Sethi, D. (2022). Like it or not! Brand communication on social networking sites triggers consumer-based brand equity.

International Journal of Consumer Studies, 46(4), 1381-1398.

Arya, V., Sethi, D., & Verma, H. (2018a). Are emojis fascinating brand values more than textual language? Mediating role of brand communication to SNS and brand attachment: An insight from India. *Corporate Communications: An International Journal*.

Aureliano-Silva, L., Strehlau, S., & Strehlau, V. (2018). The relationship between brand attachment and consumers' emotional well-being. *Journal of Relationship Marketing, 17*(1), 1-16.

Bagozzi, R. P., Romani, S., Grappi, S., & Zarantonello, L. (2021). Psychological underpinnings of brands. *Annual review of psychology, 72*, 585-607.

Belaid, S., & Temessek Behi, A. (2011). The role of attachment in building consumer-brand relationships: an empirical investigation in the utilitarian consumption context. *Journal of product & brand management, 20*(1), 37-47.

Belch, G., & Belch, M. (2019). *Advertising and Promotion–An Integrated Marketing Communication Perspective (6-month*: McGraw-Hill Education.

Bian, X., & Haque, S. (2020). Counterfeit versus original patronage: Do emotional brand attachment, brand involvement, and experience matter? *Journal of Brand Management, 27*, 438-451.

Bose, S., Pradhan, S., Bashir, M., & Roy, S. K. (2022). Customer-based place brand equity and tourism: A regional identity perspective. *Journal of travel research, 61*(3), 511-527.

Brakus, J. (2008). Experiential Attributes and Consumer Judgments,‖ in Handbook on Brand and Experience Management, Bernd H. Schmitt and David Rogers, eds. In: Northampton, MA: Edward Elgar.

Brakus, J., Schmitt, B. H., & Zarantonello, L. (2009). Brand experience: what is it? How is it measured? Does it affect loyalty? *Journal of Marketing, 73*(3), 52-68.

Brun, I., Rajaobelina, L., Ricard, L., & Amiot, T. (2020). Examining the influence of the social dimension of customer experience on trust towards travel agencies: The role of experiential predisposition in a multichannel context. *Tourism Management Perspectives, 34*, 100668.

Centeno, D., & Mandagi, D. (2022). Destination brand gestalt and its effects on brand attachment and brand loyalty. *Philippine Management Review, 29*(1), 1-24.

Chand, V. S., & Fei, C. (2021). Self-brand connection and intention to purchase a counterfeit luxury brand in emerging economies. *Journal of Consumer Behaviour, 20*(2), 399-411.

Chang, Y. P., & Dong, X. B. (2016). Research on the impact of consumer interaction behavior on purchase intention in an SNS environment: evidence from China. *Information Development, 32*(3), 496-508.

Cheung, M. L., Pires, G. D., Rosenberger, P. J., & De Oliveira, M. J. (2020). Driving consumer–brand engagement and co-creation by brand interactivity. *Marketing Intelligence & Planning, 38*(4), 523-541.

Correia Loureiro, S. M., & Kaufmann, H. R. (2012). Explaining love of wine brands. *Journal of Promotion Management, 18*(3), 329-343.

David, M. E., Carter, K., & Alvarez, C. (2020). An assessment of attachment style measures in marketing. *European Journal of Marketing, 54*(12), 3015-3049.

Diallo, M. F., Moulins, J.-L., & Roux, E. (2021). Unpacking brand loyalty in retailing: a three-dimensional approach to customer–brand relationships. *International Journal of Retail & Distribution Management, 49*(2), 204-222.

Donvito, R., Aiello, G., Grazzini, L., Godey, B., Pederzoli, D., Wiedmann, K.-P., . . . Skorobogatykh, I. I. (2020). Does personality congruence explain luxury brand attachment? The results of an international research study. *Journal of Business Research, 120*, 462-472.

Dwayne Ball, A., & Tasaki, L. H. (1992). The role and measurement of attachment in consumer behavior. *Journal of consumer psychology, 1*(2), 155-172.

Ebrahim, R. S. (2020). The role of trust in understanding the impact of social media marketing on brand equity and brand loyalty. *Journal of Relationship Marketing, 19*(4), 287-308.

Eisend, M. (2015). Have we progressed marketing knowledge? A meta-meta-analysis of effect sizes in marketing research. *Journal of Marketing, 79*(3), 23-40.

Fathima MS, A., Khan, A., & Alam, A. S. (2022). Relationship of the Theory of Consumption Values and Flow with Online Brand Experience: A Study of Young Consumers. *Journal of Internet Commerce*, 1-29.

Fedorikhin, A., Park, C. W., & Thomson, M. (2008). Beyond fit and attitude: The effect of emotional attachment on consumer responses to brand extensions. *Journal of consumer psychology, 18*(4), 281-291.

Fournier, S. (1998). Consumers and their brands: Developing relationship theory in consumer research. *Journal of Consumer Research, 24*(4), 343-373.

Gilal, F. G., Gilal, N. G., Gilal, R. G., Gong, Z., Gilal, W. G., & Tunio, M. N. (2021). The ties that bind: do brand attachment and brand passion translate into consumer purchase intention? *Central European Management Journal, 29*(1), 14-38.

Ha, H. Y., & Perks, H. (2005). Effects of consumer perceptions of brand experience on the web: Brand familiarity, satisfaction, and brand trust. *Journal of consumer behaviour: An international research review, 4*(6), 438-452.

Helal, G., Ozuem, W., & Lancaster, G. (2018). Social media brand perceptions of millennials. *International Journal of Retail & Distribution Management.*

Hemsley-Brown, J. (2023). Antecedents and consequences of brand attachment: A literature review and research agenda. *International Journal of Consumer Studies, 47*(2), 611-628.

Holbrook, M. B. (2000). The millennial consumer in the texts of our times: Experience and entertainment. *Journal of Macromarketing, 20*(2), 178-192.

Huang, R., Ha, S., & Kim, S.-H. (2018). Narrative persuasion in social media: an empirical study of luxury brand advertising. *Journal of Research in Interactive Marketing.*

Hwang, J., & Lee, J. (2019). A strategy for enhancing senior tourists' well-being perception: Focusing on the experience economy. *Journal of Travel & Tourism Marketing, 36*(3), 314-329.

Japutra, A., Ekinci, Y., & Simkin, L. (2018). Tie the knot: building stronger consumers' attachment toward a brand. *Journal of Strategic Marketing, 26*(3), 223-240.

Japutra, A., Ekinci, Y., & Simkin, L. (2019). Self-congruence, brand attachment and compulsive buying. *Journal of Business Research, 99*, 456-463.

Jasin, M. (2022). The Role of Social Media Marketing and Electronic Word of Mouth on Brand Image and Purchase Intention of SMEs Product. *Journal of Information Systems and Management (JISMA), 1*(4), 54-62.

Kaldeen, M. (2019). Impact of firm-created and user-generated social media communication on brand associations.

Karjaluoto, H., Munnukka, J., & Kiuru, K. (2016). Brand love and positive word of mouth: the moderating effects of experience and price. *Journal of product & brand management, 25*(6), 527-537.

Khan, I., & Rahman, Z. (2016). E-tail brand experience's influence on e-brand trust and e-brand loyalty: The moderating role of gender. *International Journal of Retail & Distribution Management, 44*(6), 588-606.

Khatoon, S., & Rehman, V. (2021). Negative emotions in consumer brand relationship: A review and future research agenda. *International Journal of Consumer Studies, 45*(4), 719-749.

Kim, A. J., & Ko, E. (2012). Do social media marketing activities enhance customer equity? An empirical study of luxury fashion brand. *Journal of Business Research, 65*(10), 1480-1486.

Koay, K. Y., Ong, D. L. T., Khoo, K. L., & Yeoh, H. J. (2020). Perceived social media marketing activities and consumer-based brand equity: Testing a moderated mediation model. *Asia Pacific journal of marketing and logistics*.

Lee, C. H., Sara. (2022). Can social media-based brand communities build brand relationships? Examining the effect of community engagement on brand love. *Behaviour of Information Technology 41*(6), 1270-1285.

Lee, C. T., & Hsieh, S. H. (2022). Can social media-based brand communities build brand relationships? Examining the effect of community engagement on brand love. *Behaviour & Information Technology, 41*(6), 1270-1285.

Levy, S., & Hino, H. (2016). Emotional brand attachment: a factor in customer-bank relationships. *International Journal of Bank Marketing*.

Li, Y., Lu, C., Bogicevic, V., & Bujisic, M. (2019). The effect of nostalgia on hotel brand attachment. *International Journal of Contemporary Hospitality Management*.

Lim, X.-J., Cheah, J.-H., Cham, T. H., Ting, H., & Memon, M. A. (2020). Compulsive buying of branded apparel, its antecedents, and the mediating role of brand attachment. *Asia Pacific journal of marketing and logistics, 32*(7), 1539-1563.

Lin, J., Zhou, Z., & Leckie, C. (2021). Green brand communication, brand prominence and self–brand connection. *Journal of product & brand management, 30*(8), 1148-1161.

McManus, J. F., Carvalho, S. W., & Trifts, V. (2022). The role of brand personality in the formation of consumer affect and self-brand connection. *Journal of product & brand management, 31*(4), 551-569.

Meskaran, F., Ismail, Z., & Shanmugam, B. (2013). Online purchase intention: Effects of trust and security perception. *Australian journal of basic and applied sciences, 7*(6), 307-315.

Mishra, A. S. (2019). Antecedents of consumers' engagement with brand-related content on social media. *Marketing Intelligence & Planning, 37*(4), 386-400.

Morgan-Thomas, A., & Veloutsou, C. (2013). Beyond technology acceptance: Brand relationships and online brand experience. *Journal of Business Research, 66*(1), 21-27.

NGO, T. T. A., LE, T. M. T., NGUYEN, T. H., LE, T. G., NGO, G. T., & NGUYEN, T. D. (2022). The impact of sns advertisements on online purchase intention of generation z: An empirical study of TikTok in Vietnam. *The Journal of Asian Finance, Economics and Business, 9*(5), 497-506.

Nofal, R., Calicioglu, C., & Aljuhmani, H. (2020). The impact of social networking sites advertisement on consumer purchasing decision: The mediating role of brand awareness. *International Journal of Data and Network Science, 4*(2), 139-156.

Park, C. W., MacInnis, D. J., Priester, J., Eisingerich, A. B., & Iacobucci, D. (2010). Brand attachment and brand attitude strength: Conceptual and empirical differentiation of two critical brand equity drivers. *Journal of Marketing, 74*(6), 1-17.

Paul, J. (2015). Masstige marketing redefined and mapped: Introducing a pyramid model and MMS measure. *Marketing Intelligence & Planning*.

Pedeliento, G., Andreini, D., Bergamaschi, M., & Salo, J. (2016). Brand and product attachment in an industrial context: The effects on brand loyalty. *Industrial Marketing Management, 53*, 194-206.

brand credibility on higher education institutes' brand equity in emerging countries. *Journal of Marketing Communications*, 1-26.

Pütter, M. (2017). The impact of social media on consumer buying intention. *Marketing, 3*(1), 7-13.

Rabbanee, F. K., Roy, R., & Spence, M. T. (2020). Factors affecting consumer engagement on online social networks: self-congruity, brand attachment, and self-extension tendency. *European Journal of Marketing, 54*(6), 1407-1431.

Rajaobelina, L., Prom Tep, S., Arcand, M., & Ricard, L. (2021). The relationship of brand attachment and mobile banking service quality with positive word-of-mouth. *Journal of product & brand management, 30*(8), 1162-1175.

Rose, S., Clark, M., Samouel, P., & Hair, N. (2012). Online customer experience in e-retailing: an empirical model of antecedents and outcomes. *Journal of Retailing, 88*(2), 308-322.

Santos, Z. R., Cheung, C. M., Coelho, P. S., & Rita, P. (2022). Consumer engagement in social media brand communities: A literature review. *International Journal of Information Management* 63, 102457.

Sarkar, A., & Roy, S. (2016). Validating a scale to measure consumer's luxury brand aspiration. *Journal of product & brand management, 25*(5), 465-478.

Savitri, C., Hurriyati, R., Wibowo, L., & Hendrayati, H. (2022). The role of social media marketing and brand image on smartphone purchase intention. *International Journal of Data and Network Science, 6*(1), 185-192.

Schivinski, B., & Dąbrowski, D. (2013). The impact of brand communication on brand equity dimensions and brand purchase intention through Facebook. *GUT FME Working Paper Series A. Gdansk (Poland): Gdansk University of Technology, Faculty of Management and Economics, 4*(4), 1-24.

Shimul, A. S. (2022). Brand attachment: a review and future research. *Journal of Brand Management, 29*(4), 400-419.

Shimul, A. S., Phau, I., & Lwin, M. (2019). Conceptualizing luxury brand attachment: scale development and validation. *Journal of Brand Management, 26*, 675-690.

Shrout, P. E., & Bolger, N. (2002). Mediation in experimental and nonexperimental studies: new procedures and recommendations. *Psychological methods, 7*(4), 422.

Tang, Z., Chen, L., Zhou, Z., Warkentin, M., & Gillenson, M. L. (2019). The effects of social media use on control of corruption and moderating role of cultural tightness-looseness. *Government Information Quarterly 36*(4), 101384.

Thompson, C. J., Arnould, E., & Giesler, M. (2013). Discursivity, difference, and disruption: Genealogical reflections on the consumer culture theory heteroglossia. *Marketing theory, 13*(2), 149-174.

Voorveld, H. A. (2019). Brand communication in social media: A research agenda. *Journal of Advertising, 48*(1), 14-26.

Xu, J., Wen, S.-y., & Kim, H.-k. (2021). The Impact of SNS Characteristic Elements on Customer Purchase Intention: Focusing on Chinese Beauty Industry Consumer. *Journal of Advanced Researches and Reports, 1*(3), 109-116.

Zha, D., Melewar, T., Foroudi, P., & Jin, Z. (2020). An assessment of brand experience knowledge literature: Using bibliometric data to identify future research direction. *International Journal of Management Reviews, 22*(3), 287-317.

Zhang, Z., & Patrick, V. M. (2021). Mickey D's has more street cred than McDonald's: Consumer brand nickname use signals information authenticity. *Journal of Marketing, 85*(5), 58-73.

Zubair, A., Baharun, R., & Kiran, F. (2022). Role of traditional and social media in developing consumer-based brand equity. *Journal of Public Affairs, 22*(2), e2469.