Advanced Hybrid Learning Architecture for Precision Cardiovascular Risk Assessment

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ABSTRACT

Remaining the major motive of demise worldwide, cardiovascular diseases (CVDs) spotlight the urgent need of accurate computational threat prediction fashions. The use of a complete heart disease Dataset obtained from 1,190 patients across 5 different databases, this work presents a twin-stage stacked machine learning (ML) approach for predicting heart diseases. Eleven important traits within the dataset are absolutely essential for risk evaluation. Randomized seek CV and Grid seek CV were used for hyperparameter optimization among all algorithms in order to guarantee strong model performance. To improve forecast accuracy, the proposed framework combines several ML classifiers consisting of ensemble techniques. With an accuracy of 99.0%, a voting Classifier including a Bagging Classifier with Random forest (RF) and decision Tree (DT) confirmed better overall performance. This result emphasizes how well combined approaches handle the complexity of coronary heart disease prediction. Early intervention and higher clinical decision-making in cardiovascular healthcare are made possible by the suggested scalable and dependable answer.

Keywords: Cardiovascular disease (CVD), extreme gradient boost (XGB), hyper-parameter tuning, heart disease, random forest classifier, stacking ensemble technique.

1. INTRODUCTION:

The heart, a key organ for circulating blood throughout the body, is vital for sustaining life. Nonetheless, dangers to its health present substantial issues, resulting in numerous problems and a chief global health burden. "Heart disease (HD)" is the foremost reason of mortality, predominantly on account of unexpected strokes and heart assaults, responsible for kind of 17.9 million deaths in step with year and constituting 32% of all worldwide fatalities [1]. "Coronary heart disease (CHD)" is the maximum not unusual shape of heart disease and a main factor in global mortality costs. Additional types of cardiac sickness encompass arrhythmias, valvular disorder, cardiomyopathies, infections, vascular diseases, and congenital anomalies. These disorders present with signs including dizziness, syncope, bradycardia or tachycardia, and dyspnea, which may result in serious complications if not detected or handled. Notwithstanding its potentially fatal nature, heart ailment can regularly be averted through lifestyle changes, together with steady bodily hobby, meditation, and a balanced, nutritional diet.

In contemporary healthcare, "machine learning (ML) and deep learning (DL)" have come to be formidable units for the prognosis and classification of intricate disorders which includes coronary heart disease. those state-of-the-art computational techniques provide unique and efficient detection of cardiovascular disorders, becoming them essential in medical diagnostics. Cardiovascular disease constitutes not only a fitness challenge but additionally imposes a substantial economic impact globally. Through 2035, the global expenditure on coronary heart ailment control is predicted to surpass $1 trillion. Inside the america, around $229 billion became expended yearly on healthcare prices related to heart disorder from 2017 to 2018. Minimizing those prices whilst enhancing diagnostic precision has emerged as a focus in clinical studies.

Researchers have extensively utilized trendy machine learning methodologies to tackle these issues, employing different attributes to forecast the possibility of cardiac disease in people [4], [5], [6]. These models utilize patient-specific facts to improve risk prediction and facilitate early intervention, potentially reducing treatment costs and improving patient outcomes. The increasing incidence of heart disease and its associated fees make the incorporation of "machine learning" in healthcare a pivotal opportunity. It facilitates accurate diagnosis and enhances tailored treatment planning, thereby advancing cardiac care and decreasing loss of life fees. Therefore, the continued research and application of "machine learning" approaches are vital for enhancing heart disease prediction and prevention [11].

2. OBJECTIVES:

(1) To develop a robust computational model for heart disease prediction using a comprehensive dataset of 1,190 patients collected from five different sources, ensuring diverse and representative data for risk analysis.
(2) To identify and utilize eleven critical features essential for cardiovascular risk assessment, enhancing the interpretability and relevance of the predictive framework.
(3) To optimize machine learning model performance through hyperparameter tuning using Randomized Search CV and Grid Search CV, enabling more accurate and reliable predictions.
(4) To implement a two-stage stacked machine learning approach combining multiple classifiers, where a voting classifier integrating Bagging, Random Forest, and Decision Tree achieved a high accuracy of 99.0%, supporting improved early diagnosis and clinical decision-making.

3. REVIEW OF LITERATURE/ RELATED WORKS:

The high incidence of cardiac disease has led to vast research focused on utilizing modern computational methods, especially "machine learning (ML)", to enhance detection and prediction precision. Numerous studies have investigated various "machine learning (ML) and deep learning (DL)" techniques to improve diagnostic accuracy for cardiac disease. Tao et al. [5] proposed the identity and localization of ischemic heart disease the usage of magnetocardiography and machine learning algorithms. This take a look at illustrated the efficacy of machine learning in processing magnetocardiographic data to detect and localize ischemia zones, presenting a novel method for cardiac diagnostics. Ozcan and Peker [25] utilized a classification and regression tree algorithm for coronary heart disorder modeling, emphasizing the efficacy of choice-tree-primarily based methods in managing intricate patient datasets and producing dependable predictions.
Latha and Jeeva [27] have examined the usage of ensemble classification algorithms to enhance the precision of coronary heart ailment threat prediction. Their research highlighted the benefits of integrating multiple classifiers to reduce overfitting and enhance typical predictive robustness. building upon this perception, Atallah and Al-Mousa [29] applied a majority voting ensemble method, integrating many machine learning classifiers to enhance performance in heart disease identification. This strategy demonstrated the efficacy of ensemble strategies in addressing the range of patient statistics.
Kavitha et al. [11] performed another study that offered a hybrid machine learning version the use of various algorithms for heart disorder prediction, demonstrating that the intentional amalgamation of algorithms can enhance diagnostic precision and interpretability. Haq et al. [31] evaluated the anticipated efficacy of various machine learning classifiers, providing a comparative analysis in their overall performance in heart ailment detection systems. Their research emphasized the significance of classifier choice and feature optimization in attaining dependable results.

Mine, solar, and Wang [33] introduced an enhanced ensemble learning methodology for forecasting coronary heart disease risk, utilizing feature engineering techniques to optimize enter data and augment the efficacy of ensemble models. Asif et al. [15] employed an ensemble machine learning technique, concentrating on the integration of models with complementary strengths to correctly forecast cardiac disease. Their research emphasized the importance of ensemble learning in mitigating data unpredictability and accomplishing superior expected accuracy.
These research mutually spotlight the transformational ability of machine learning in predicting cardiac disorder. They underscore the significance of state-of-the-art algorithms, ensemble methods, and characteristic engineering in improving diagnostic accuracy. This studies seeks to beautify system mastering tactics by making use of twin-stage stacked models and hyperparameter optimization to enhance prediction accuracy for cardiac diseases, building upon present fundamental efforts.

Table 1: Comparison Table for Related Work

Sl.No	Area & Focus of the Research	The result of the Research	Reference
1	Global overview and burden of cardiovascular diseases	Identified CVDs as the leading cause of death globally, emphasizing the need for prevention	D. T. Khan, WHO (2022) [1]
2	Statistical facts and impact of heart disease in the U.S. population	Highlighted heart disease as the primary cause of death in the U.S. with key risk factors	U.S. Department of Health & Human Services (2022) [3]
3	Comprehensive heart disease dataset for machine learning research	Provided a rich dataset with 1,190 patient records from five sources for robust prediction	M. Siddhartha, IEEE DataPort (2020) [7]
4	Heart disease prediction using hybrid machine learning models	Achieved high prediction accuracy through a hybrid ML framework integrating multiple models	M. Kavitha et al., ICICT (2021) [11]
5	Heart disease prediction using ensemble learning techniques	Demonstrated improved prediction performance using ensemble methods like voting classifiers	K. Yuan et al., DSA (2020) [13]

4. MATERIALS AND METHODS:

The proposed approach presents a twin-stage stacked machine learning model to forecast cardiac disease utilizing the heart disease Dataset [7], comprising eleven critical variables from 1,190 patients across five databases. This method employs many machine studying strategies, including "Random forest (RF), decision Tree (DT), Logistic Regression (LR), support Vector machine (SVM), and extreme Gradient boost (XGB)", optimized through Randomized seek CV and Grid search CV to acquire most useful hyperparameter settings. The system makes use of an ensemble studying approach, incorporating a voting Classifier that merges a Bagging Classifier with Random forest and decision Tree, which exhibited super predictive accuracy. The version leverages the benefits of many classifiers in a two-stage stacking method, efficiently tackling the intrinsic complexity of cardiac data. This cautioned machine seeks to improve threat prediction by way of using advanced machine learning techniques, supplying a scalable and excessive-performance answer for the early prognosis and improved management of cardiovascular illnesses.

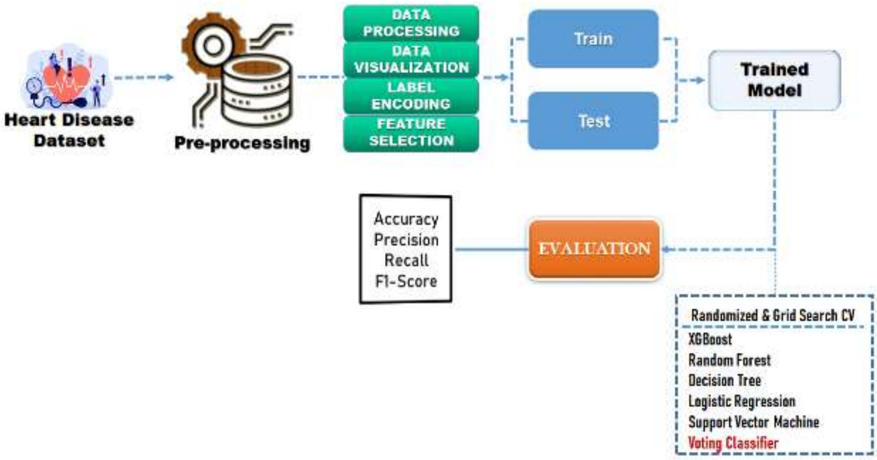


Fig 1: Proposed Architecture

This graphic depicts a standard "machine learning" model for predicting cardiac disease. The method commences with the heart disease dataset [7], which is subjected to pre-processing for modeling practise. The dataset is ultimately divided into schooling and checking out subsets. More than one machine learning models, such as "Random forest, selection Tree, Logistic Regression, and support Vector machine", are skilled using the education facts. The skilled models are assessed at the testing data utilizing metrics such as "accuracy, precision, recall, and F1-score". A voting classifier is employed to amalgamate the predictions of various models to enhance accuracy.

4.1 Dataset Collection:

This study utilizes a dataset consisting of 1,190 entries, encompassing 12 pertinent variables associated with heart disease prediction. The data encompasses demographic records (age, sex), clinical metrics "(resting blood pressure, cholesterol levels, maximum heart rate)", and diagnostic criteria "(form of chest pain, fasting blood glucose, resting electrocardiogram, ST segment slope, oldpeak, and exercise-induced angina)". The target variable indicates the existence or non-existence of cardiac disease. The dataset is meticulously organized, devoid of missing values, comprising 11 integer capabilities and one waft for accurate analysis.

Table 2: DatasetDF1 Collection Table

	age	sex	chest pain type	resting bp s	cholesterol	fasting blood sugar	resting ecg	max heart rate	exercise angina	oldpeak	ST slope
0	40	1	2	140	289	0	0	172	0	0.0	1
1	49	0	3	160	180	0	0	156	0	1.0	2
2	37	1	2	130	283	0	1	98	0	0.0	1
3	48	0	4	138	214	0	0	108	1	1.5	2
4	54	1	3	150	195	0	0	122	0	0.0	1

This study employs a dataset including 1,000 entries and 13 characteristics, encompassing each demographic and clinical data. The analysis covers multiple variables including age, gender, chest pain, blood pressure, serum cholesterol, fasting blood sugar, relaxing electrocardi results, maximum heart rate, exercise science angina, oldpec, stroke, primary vessels to establish the presence of target variable heart disease. The dataset is comprehensive, devoid of missing numbers, predominantly comprising integer facts types, with a float type designated for oldpeak.

Table 3: Dataset DF 2 Collection Table

	patientid	age	gender	chestpain	restingBP	serumcholestrol	fastingbloodsugar
0	103368	53	1	2	171	0	0
1	119250	40	1	0	94	229	0
2	119372	49	1	2	133	142	0
3	132514	43	1	0	138	295	1
4	146211	31	1	1	199	0	0

4.2 Pre-Processing:

In the pre-processing phase, i will address essential procedures such as data processing, data visualization, label encoding, and feature selection. These processes are essential for dataset preparation, enhancing its quality, and ensuring its suitability for powerful model training.

4.2.1 Data Processing

The dataset is imported into a pandas Data Frame for efficient manipulation and analysis. Irrelevant columns, such as identifiers or irrelevant attributes, are eliminated to optimize the dataset and reduce noise. This level ensures the retention of best the vital functions, together with age, sex, cholesterol, and heart charge, for analysis and model training, thereby retaining focus at the determinants of heart disease outcomes.

4.2.2 Visualization

Seaborn and Matplotlib facilitate the visualization of the dataset, aiding in the identification of styles and relationships among variables. various visualizations, such as histograms, boxplots, heatmaps, and pair plots, are produced to analyze feature distributions and their intercorrelations. statistics visualization allows comprehension of underlying traits, identification of outliers, and evaluation of the need for extra facts preprocessing, while also offering insights that might tell feature engineering for model development.

4.2.3 Label Encoding

Label Encoding is applied for categorical variables in the dataset, transforming them into numerical values for machine learning models. This is in particular beneficial for variables such as gender, chest ache kind, and exercise-brought on angina, which encompass categorical data. LabelEncoder assigns a distinct integer value to every unique category, facilitating effective processing of these features by using algorithms. This guarantees that the data is ready for input into machine learning models, which often necessitate numerical inputs for executing classification and regression tasks.

4.2.4 Feature selection

feature selection is conducted to ascertain the most significant variables that influence the prediction of heart disease. Methods such as correlation analysis, mutual data, and recursive feature elimination are utilized to dispose of redundant or irrelevant features. Concentrating on the essential factors diminishes the version's complexity, ensuing in expedited training periods and enhanced performance. This degree ensures that the model utilizes just the most pertinent data, hence improving both accuracy and interpretability in heart disease prediction.

4.3 Training & Testing:

The training and testing levels consist of partitioning the dataset into training and testing subsets to assess version efficacy. The training set is applied to expand the version, even as the trying out set is allocated for assessing its efficacy on novel data. Diverse methodologies, inclusive of as cross-validation and hyperparameter optimization, are utilized to assure resilient and generalized learning. This procedure guarantees that the model can precisely forecast results based on empirical data.

4.4 Algorithms:

XGBoostis utilized for its advanced speed and predictive precision in assessing heart disease risk. This approach [16] use gradient boosting to augment version overall performance by mitigating overfitting and enhancing generalization. Its capacity to manipulate extensive datasets and combine regularization renders it top-quality for dependable heart disease forecasts.
Random Forest is employed to construct an ensemble of decision trees, improving predictive accuracy and resilience to overfitting. This technique [17] averages the findings of numerous trees to become aware of difficult patterns in the heart disease dataset, yielding dependable insights into patient threat variables and enhancing overall classification efficacy.
Decision Tree is utilized for its interpretability and capacity to build intricate interactions within the coronary heart disease dataset [7]. This algorithm [18] recursively divides the input according to feature values, facilitating distinct decision-making routes. The clear representation facilitates comprehension of the principal determinants of heart disease risk.
Logistic Regression is employed for its efficacy in binary classification tasks, especially in forecasting the existence of cardiac disease. This method [19] models the probability of a binary result, supplying clean insights into the influence of several elements on coronary heart disease risk, therefore enhancing decision-making efficacy.
Support Vector Machine is utilized to categorize heart disease risk by identifying the best hyperplane that distinguishes classes within the dataset [20]. Its capacity to control excessive-dimensional facts and deliver reliable performance renders it a crucial instrument for identifying people at risk of coronary heart disease.
Voting Classifier (Bagging Classifier with RF + DT): The voting Classifier amalgamates the advantages of both Random forest and decision Tree algorithms to improve predictive accuracy. This ensemble approach consolidates findings, making use of various perspectives on the records, which enhances robustness and reliability in identifying people at danger for heart disease.

5. RESULTS AND DISCUSSION:

Accuracy:A test demonstrates accuracy through its capacity to differentiate correctly between patient cases and healthy cases. Testing accuracy requires determining the relationship between true positive and true negative results among all examined cases. It can be expressed mathematically:

$$"Accuracy = \frac{\mathrm{TP + TN}}{\mathrm{TP + FP + TN + FN}} (1)"$$

Precision: The accuracy takes person designated as positive's share of precisely classified cases into account. It is so stated as a formula for computing accuracy:

$$"Precision = \frac{\text{True Positive}}{\text{True Positive } + \text{False Positive}} (2)"$$

Recall: Recall that in machine learning there is a computation based on a model's capacity to identify all pertinent times in a given class. The link between exactly predicted positive comments for overall true positivity offers understanding of the impact of a version to pinpoint the events in a given class.

$$"Recall = \frac{\mathrm{TP}}{\mathrm{TP + FN}} (3)"$$

F1-Score: The F1 point sum is a computation applied to assess the "machine learning" model's correctness. It generates a version combining accuracy with misses the matrix. The frequency of suitable predictions made by a model over the data set is found using the accuracy meter.

$$"F1\,Score = 2 * \frac{Recall\ \mathrm{X}\ Precision}{Recall + Precision} * 100(1)"$$

Cohen Kappa:"Cohen's Kappa (κ)" is a statistical metric employed to assess the degree of concordance between two evaluators who categorize objects into distinct classifications. It's far in particular advantageous in scenarios when decisions are subjective and the categories are nominal, lacking a natural order.

$$\text{"}Kappa(k) = \frac{P_o - P_e}{1 - P_e}\text{"}$$

Table 4: Performance Evaluation Metrics-DF2

ML Model	Accuracy	Precision	Recall	F1-Score	Cohen Kappa	ROC AUC Score
XGBoost	0.945	0.951	0.940	0.962	0.889	0.977
RF	0.954	0.958	0.948	0.969	0.906	0.972
DT	0.908	0.913	0.950	0.878	0.815	0.911
LR	0.832	0.848	0.842	0.855	0.660	0.906
SVM	0.727	0.739	0.780	0.702	0.454	0.782
XGB-RS-CV	0.929	0.936	0.925	0.947	0.855	0.974
RF-RS-CV	0.941	0.947	0.940	0.954	0.881	0.967
DT-RS-CV	0.861	0.871	0.895	0.847	0.722	0.911
LR-RS-CV	0.836	0.852	0.848	0.855	0.669	0.906
SVM-RS-CV	0.870	0.885	0.862	0.908	0.735	0.935
XGB-GS-CV	0.912	0.923	0.893	0.954	0.820	0.958
RF-GS-CV	0.933	0.940	0.926	0.954	0.864	0.961
DT-GS-CV	0.790	0.808	0.814	0.802	0.576	0.883
LR-GS-CV	0.836	0.852	0.848	0.855	0.669	0.906
SVM-GS-CV	0.866	0.881	0.856	0.908	0.726	0.933
Meta Model	0.929	0.936	0.919	0.954	0.855	0.970
Voting Classifier	0.975	0.977	0.977	0.977	0.949	0.970

Table 1emphasizes the efficacy of distinct machine learning fashions and their variations, concentrating on metrics such as "accuracy, precision, recall, F1 score, Cohen's Kappa, and ROC AUC". It highlights comparisons between the fundamental models and their augmented variants through regularization and cross-validation.

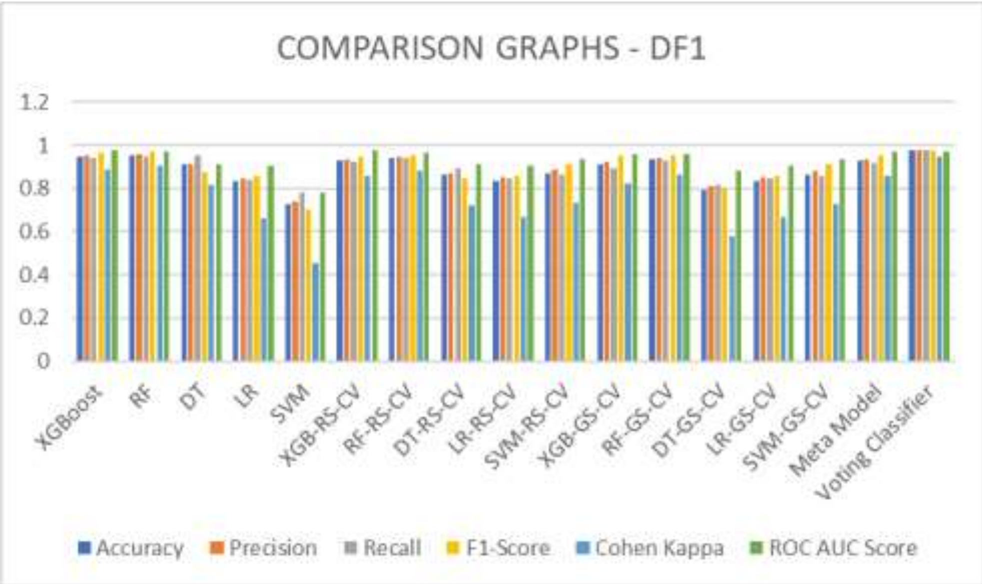
Table 5: Performance Evaluation Metrics – DF2

ML Model	Accuracy	Precision	Recall	F1-Score	Cohen Kappa	ROC AUC Score
XGBoost	0.970	0.974	0.974	0.974	0.938	0.998
RF	0.985	0.987	0.991	0.983	0.969	0.999
DT	0.960	0.966	0.950	0.983	0.917	0.955
LR	0.950	0.958	0.935	0.983	0.896	0.994
SVM	0.850	0.870	0.885	0.855	0.693	0.915
XGB-RS-CV	0.945	0.952	0.965	0.940	0.887	0.995
RF-RS-CV	0.980	0.983	0.983	0.983	0.959	0.999
DT-RS-CV	0.965	0.970	0.974	0.966	0.928	0.990
LR-RS-CV	0.945	0.954	0.934	0.974	0.886	0.993
SVM-RS-CV	0.955	0.961	0.966	0.957	0.907	0.982
XGB-GS-CV	0.950	0.957	0.965	0.949	0.897	0.995
RF-GS-CV	0.975	0.979	0.983	0.974	0.949	0.998
DT-GS-CV	0.935	0.945	0.933	0.957	0.865	0.974

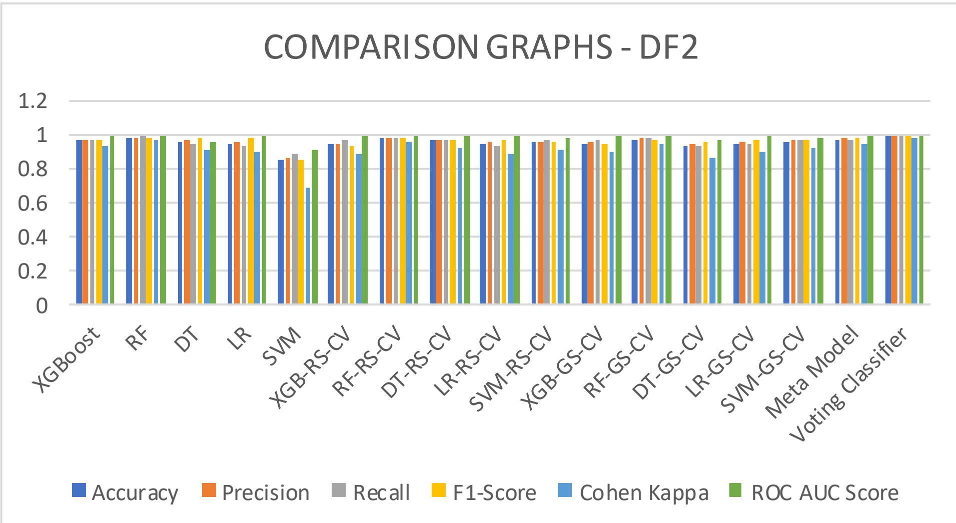
LR-GS-CV	0.950	0.958	0.942	0.974	0.896	0.994
SVM-GS-CV	0.960	0.966	0.966	0.966	0.918	0.983
Meta Model	0.975	0.979	0.975	0.983	0.948	0.998
Voting Classifier	0.990	0.991	0.991	0.991	0.979	0.990

Table 2displays the efficacy of machine learning models alongside ensemble methods, emphasizing "accuracy, precision, recall, F1 score, Cohen's Kappa, and ROC AUC". It highlights the enhanced performance attained through the integration of numerous models, demonstrating the advantages of ensemble techniques.

Graph 1: Comparison Graphs – DF1



Graph 2: Comparison Graphs –DF2



Graphs 1 and 2 compare diverse machine learning algorithms the usage of performance metrics: accuracy in sky blue, "precision in orange, recall in gray, F1-rating in yellow, Cohen Kappa in blue, and ROC AUC" rating in light green. The balloting Classifier surpasses all other algorithms in these criteria, as illustrated in the graphs.

6. CONCLUSION:

The examination of heart disease prediction [11] highlights the efficacy of utilizing contemporary system learning methodologies to attain precise and dependable results. This work utilizes a complete dataset of eleven key variables from 1, one hundred ninety patients, obtained from several assets, to demonstrate the transformative potential of machine learning in heart disease threat evaluation. The twin-level stacking machine learning method, coupled with complete hyperparameter optimization using Randomized search CV and Grid seek CV, ensures robust model performance. The ensemble voting Classifier, which integrates a Bagging Classifier with Random wooded area and choice Tree, attained the maximum accuracy of 99.zero%, demonstrating its proficiency in managing the dataset's complexities. This final results corroborates the function of ensemble methods in improving predictive accuracy and dependability. The suggested system provides a scalable and efficient approach for the early prognosis of cardiovascular illnesses, facilitating timely clinical interventions and enhancing patient outcomes. These discoveries appreciably advance the area of healthcare analytics, illustrating the capacity of machine learning in tackling essential healthcare issues.

The future scopethis study entails augmenting the dataset to include a broader range of patient profiles and clinical histories for improved generalization. Incorporating deep learning methodologies, such as neural networks, can also increase predictive precision. moreover, real-time statistics processing and implementation in healthcare environments thru cell packages or wearable devices will facilitate the early identification of cardiovascular problems, imparting individualized monitoring and prompt remedies, hence enhancing preventative healthcare and patient management.

REFERENCES:

[1] Wang, Y., Zhang, A., Zhang, P., & Wang, H. (2019). Cloud-assisted EHR sharing with security and privacy preservation via consortium blockchain. *IEEE Access*, 7(3), 136704-136719.

[2] Viswanath, G. (2024). Personalized Breast Cancer Prognosis through Data Mining Innovations. *Cuestiones de Fisioterapia*, 53(2), 538-548.

[3] Ray, P. P., Dash, D., Salah, K., & Kumar, N. (2021). Blockchain for IoT-based healthcare: Background consensus platforms and use cases. *IEEE Syst. J.*, 15(1), 85-94.

[4] Viswanath, G. (2021). Adaptive Light Weight Encryption Algorithm for Securing Multi-Cloud Storage. *Turkish Journal of Computer and Mathematics Education*, 12(9), 545-554.

[5] Tao, R., Zhang, S., Huang, X., Tao, M., Ma, J., Ma, S., Zhang, C., Zhang, T., Tang, F., Lu, J., Shen, C., & Xie, X. (2019). Magnetocardiography-based ischemic heart disease detection and localization using machine learning methods. *IEEE Trans. Biomed. Eng.*, 66(6), 1658–1667.

[6] Viswanath, G. (2023). A Real -Time Video Based Vehicle Classification Detection And Counting System. *Industrial Engineering Journal*, 52(9), 474-480.

[7] Jiang, M., & Qin, X. (2022). Distributed ledger technologies in vehicular mobile edge computing: A survey. *Complex Intell. Syst.*, 8(5), 4403-4419.

[8] Viswanath, G. (2025). Proactive Security in Multi-Cloud Environments: A Blockchain Integrated Real-Time Anomaly Detection and Mitigation Framework. *Cuestiones de Fisioterapia*, 54(2), 392-417.

[9] Esfahani, H. A., & Ghazanfari, M. (2017). Cardiovascular disease detection using a new ensemble classifier. *IEEE 4th Int. Conf. Knowl.-Based Eng. Innov. (KBEI)*, 2017(1), 1011–1014.

[10] Viswanath, G. (2024). International Journal of Information Technology and Computer Engineering. *International Journal of Interpreting Enigma Engineers (IJIEE)*, 12(3), 647-657.

[11] Kavitha, M., Gnaneswar, G., Dinesh, R., Sai, Y. R., & Suraj, R. S. (2021). Heart disease prediction using hybrid machine learning model. *6th Int. Conf. Inventive Comput. Technol. (ICICT)*, 2021(1), 1329–1333.

[12] Viswanath, G. (2024). Machine Learning for IoT Device Anomaly Detection Attack Classification. *International Journal of Mechanical Engineering Research and Technology*, 16(9), 66-76.

[13] Chattaraj, D., Bera, D., Das, A. K., Saha, S., Lorenz, P., & Park, Y. (2021). Block-CLAP: Block chain-assisted certificate less key agreement protocol for Internet of Vehicles in smart transportation. *IEEE Trans. Veh. Technol*., 70(8), 8092-8107.

[14] Viswanath, G.(2024). A Hybrid Particle Swarm Optimization And C4.5 For Network Intrusion Detection And Prevention System. *International Journal of Computing This link is disabled*, 23(1), 109-115.

[15] Khan, M. B., Yang, Z. S., Lin, C. Y., Hsu, M. C., Urbina, A. N., Assavalapsakul, W., Wang, W.,H., Chen, Y. H., & Wang, S. F. (2023). Dengue overview: An updated systemic review. *J. Infection Public Health*, 16(10), 1625–1642.

[16] Viswanath, G. (2014). Distributed Utility-Based Energy Efficient Cooperative Medium Access Control in MANETS. *International Journal of Engineering Inventions*, 4(2), 08-12.

[17] Kabir, M. A., Zilouchian, H., Younas, M. A., & Asghar, W.(2021). Dengue detection: Advances in diagnostic tools from conventional technology to point of care. *Biosensors*, 11(7), 206-212.

[18] Abdualgalil, B., Abraham, S., & Ismael, W. M. (2022). Early diagnosis for dengue disease prediction using efficient machine learning techniques based onclinical data. *J. Robot. Control (JRC)*, 3(3), 257–268.

[19] Chaw, J. K., S. Chaw, S. H., Quah, C. H., Sahrani, S., Ang, M. C., Zhao, Y., & Ting, T. T. (2024). A predictive analytics model using machine learning algorithms to estimate the risk of shock development among dengue patients. *Healthcare Anal.*, 5(2), 1–17.

[20] Sarwar, M. T., & Mamun, M. A. (2022). Prediction of dengue using machine learning algorithms: Case study Dhaka. *Proc. 4th Int. Conf. Electr., Comput. Telecommun. Eng. (ICECTE)*, 2(1), 1–6.

[21] Ali, N. (2024). The recent burden of dengue infection in bangladesh: A serious public health issue. *J. Infection Public Health*, 17(2), 226–228.

[22] Viswanath, G. (2021). Hybrid encryption framework for securing big data storage in multi-cloud environment. *Evolutionary intelligence*, 14(2), 691-698.

[23] Davi, C., Pastor, A., Oliveira, T., Neto, F. B. d. L., Braga-Neto, U., Bigham, A. W., Bamshad, M., Marques, E. T. A., & Acioli-Santos, B. (2019). Severe dengue prognosis using human genome data and machine learning. *IEEE Trans. Biomed. Eng*., 66(10), 2861–2868.

[24] Viswanath, G. (2023). A Real-Time Case Scenario Based On URL Phishing Detection Through Login URLS. *Material science and technology*, 22(9), 103-108.

[25] Ozcan, M., & Peker, S. (2023). A classification and regression tree algorithm for heart disease modeling and prediction. *Healthcare Analytics*, 3(1), 1-9.

[26] Viswanath, G., & Sunil Kumar Reddy, T. (2014). Enhancing power unbiased cooperative media access control protocol in manets. *International Journal of Engineering Inventions*, 4(9), 8-12.

[27] Latha, C. B. C., & Jeeva, S. C. (2019). Improving the accuracy of prediction of heart disease risk based on ensemble classification techniques. *Informat. Med. Unlocked*, 16(1), 1-9.

[28] Viswanath, G. (2024). Artificial Intelligence-driven Frameworks for Fostering Active Participation and Learning in Language Classrooms. *International Journal of Interpreting Enigma Engineers (IJIEE)*, 1(3), 23-32.

[29] Dey, S. K., Rahman, M. M., Howlader, A., Siddiqi, U. R., Uddin, K. M. M., Borhan, R., & Rahman, E. U. (2022). Prediction of dengue incidents using hospitalized patients, metrological and socio-economic data in Bangladesh: A machine learning approach. *PLoS One*, 17(7), 1-7.

[30] Viswanath, G. (2024). Improved LightGBM Model Performance Analysis and Comparison For Coronary Heart Disease Prediction. *International Journal of Information Technology and Computer Engineering*, 12(3), 658-672.

[31] Bui, H. T., Hamamoto, K., & Paing, M. P. (2022). Tooth localization using YOLOv3 for dental diagnosis on panoramic radiographs. *IEEJ Trans. Electron., Inf. Syst.*, 142(5), 557–562.

[32] Viswanath, G. (2024). Hybrid Feature Extraction With Machine Learning To Identify Network Attacks. *International Journal of HRM and Organizational Behavior*, 12(3), 217-228.

[33] Mienye, I. D., Sun, Y., & Wang, Z. (2020). An improved ensemble learn ing approach for the prediction of heart disease risk. *Informat. Med. Unlocked*, 20(1), 1-5.

[34] Viswanath, G. (2023). A Real Time Online Food Ording Application Based Django Restfull Framework. *Juni Khyat*, 13(9), 154-162.

[35] Yasa, Y., Çelik, O., Bayrakdar, I. S., Pekince, A., Orhan, K., Akarsu, S., Atasoy, S., Bilgir, E., Odabas, A., & Aslan, A. F.(2020). An artificial intelligence proposal to automatic teeth detection and numbering in dental bite-wing radiographs. *Acta Odontologica Scandinavica*, 79(4), 275–281.

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