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A hybrid intelligent model for prediction of coronary artery diseases using TabNet and multiclass SVM

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ABSTRACT

Cardiovascular disease is one of the significant fatality-causing diseases in this era by affecting the heart and blood vessels. Cardio diseases are classified into coronary heart disease (CHD), heart failure, valve disease, and arrhythmias. Medical diagnosis of heart disease and treating the patient is a challenging process, where early detection can lead to decreased fatality. In this research, hybrid model-based prediction of CHD detection is developed by TabNet and multiclass support vector machine (SVM). We created our datasets for experimentation by visiting the hospitals in the Mysore and Mandya regions of Karnataka, India. Datasets consist of 16 features; the features are pre-processed to normalize, encode, and handle missing values to extract the aggregate features using TabNet, and the multiclass SVM model is trained to classify the disease based on the classes. The proposed hybrid model prediction performance was evaluated using various metrics such as accuracy, recall, precision, and F1-score.

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1. INTRODUCTION

Nowadays, heart disease is the primary disease in both men and women, which affects the function and structure of the heart, leading to death. These are broadly classified into coronary heart disease (CHD), heart failure, valve disease, and arrhythmias [1]. Generally, the heart is the size of a fist, and it beats 72 times per minute for an average person by circulating blood vessels around it. The minute blood vessels constitute the blood and oxygen required for the functioning of the heart. The narrowing of blood vessels flowing to the heart leads to CHD, also called coronary artery disease (CAD). A condition in which the heart muscle doesn't pump enough blood to the heart leads to abnormal heart functioning called heart failure (systolic and diastolic). The four types of heart valves are mitral, tricuspid, aortic, and pulmonary, which look for blood to flow in only one direction properly with the open/closed valve all the way. When any or more of the heart valves fail to function, it leads to valve diseases called regurgitation, stenosis, and artesia. Usually, the heart rate remains constant in humans except in exceptional conditions such as during physical activity, when it may beat quickly, and while sleeping, when it beats slowly. If the heart beats too quickly or slowly during a person's regular activity, it leads to an irregular rhythm called arrhythmias. Presently, the diagnoses of heart disease are done using an array of laboratory tests and imaging studies like electrocardiogram (ECG), holter monitoring, echocardiogram, exercise or stress tests, cardiac catheterization, cardiac CT scan and cardiac magnetic resonance imaging (MRI) scan [2]. All these tests require time for the physician to treat the patient by knowing the test results. The patient's condition is crucial, and an accurate diagnosis is necessary to save the human life within that stipulated period. So here, we need a prediction model to predict heart diseases in humans, which gives more time for the physician to treat the patient and enforce the modern machine learning technology (ML).

ML plays a crucial role in detecting and predicting human heart diseases [3]. It is one of the most challenging tasks to predict heart disease due to its more dependent 16 parameters such as blood pressure, hyperlipidemia, body mass, sex, age, triglyceride, HDL, LDL, heart rate, creatinine, diagnosis, family history, smoking, diabetes, cholesterol, and glucose. Predicting the future risk of the progression of heart disease helps patients take precautionary measures, and physicians opt for specific treatment by making priority decisions. Predictive models can be classified into two categories: classification models and regression models, which perform based on statistical analysis and data mining techniques [4]. The most commonly used predictive models are developed from regression, decision trees (DT), and neural networks. Other classifiers such as clustering, time series, outlier detection, ensemble, factor analysis, Naïve Bayes, and support vector machine (SVM) can also be used [5]. Each classifier uniquely approaches the data, so choosing suitable classifiers for the model is challenging for the researchers.

In this research, we aim to develop a human CAD prediction model, considering 16 parameters that directly or indirectly cause risk to the heart. Hybrid learning algorithms, which integrate multiple weak models into a robust framework, facilitate comprehensive exploration of intricate interconnections among diverse features within constrained feature values and sample sizes. This approach enhances the predictive model's assessment metrics and delivers valuable supplementary assistance for CAD diagnosis [6]. It helps to provide customized therapy for patients with sufficient time for the physician to take appropriate measures by enhancing overall cardiac care and optimizing resource allocation [7]. The dataset used for experimentation was collected in and around the hospitals located in Mysore and Mandya regions, Karnataka, India. Datasets were computed and analyzed on Google Colab using Python [8].

2. LITERATURE SURVEY

Many eminent researchers in ML have attempted to predict human heart diseases. Heart diseases are most of the dominant diseases leading to mortality in developed nations. The most relevant work carried out so far in the prediction of heart diseases in humans is discussed here.

Uddin *et al.* [9] developed a model to diagnose cardiovascular diseases using a ML approach. For the experimentation, three dataset categories were collected from the heart disease dataset Repository University of California Irvine (UCI) containing 14 attributes, IEEE DataPort containing 12 attributes, and Kaggle containing 12 attributes. The authors implemented ML models like SVM, random forest (RF), multilayer perceptron (MLP), DT, extreme gradient boost (XGBoost), gradient boosting, and light gradient boosting machine classifier to classify heart diseases. Before applying the datasets to processing, pre-processing stages like cleaning, transformation, integration, and reduction were carried out. The model's performance was evaluated through precision, recall, accuracy rate, receiver operating characteristics (ROC) curve, and F1-score. The DT model outperforms other models for the combined datasets of UCI, IEEE, and Kaggle.

Ali *et al.* [10] aimed at developing supervised ML algorithms for the prediction of heart diseases and compared the model's performance for the highest accuracy. For experimentation purposes, a dataset from the Kaggle contained 14 attributes of 1,025 patients, including 312 females and 713 males with and without diseases. To classify heart diseases, the authors implemented six ML algorithms like RF, K-nearest neighbors (KNN), MLP, DT, AdaboostM1, and logistic regression (LR) classifiers. The datasets were pre-processed by applying a filter to replace missing values known as the interquartile range (IQR) to get better statistical and analytical results. The classification algorithms were evaluated through precision, recall, F-measure, sensitivity, specificity, and kappa metrics. The RF, KNN, and DT perform better than other classification algorithms.

Gao *et al.* [11] worked on enhancing the performance of the heart disease prediction model with the ensemble learning method. For experimentation purposes, 1,025 datasets were collected containing 13 features to classify for heart disease and non-heart disease from the Cleveland heart disease dataset. The authors implemented the proposed model using four ML algorithms, such as KNN, DT, RF and Naïve Bayes and two ensemble algorithms, boosting and bagging, to classify hearts as healthy or unhealthy. The datasets were pre-processed to delete the missing values and extracted features using linear discriminant analysis (LDA) and principal component analysis (PCA). Out of which, 75% of the datasets were used for training the model using nine-fold cross-validation, and 25% were used to test the model using evaluation metrics, namely accuracy, recall, F-score, ROC, area under the curve (AUC) and precision. The two ensemble algorithms perform better than other ML algorithms for the PCA feature extraction method.

Chang *et al.* [12] developed an artificial intelligence model to detect heart disease using ML algorithms. For experimentation purposes, the datasets were collected from the patient's medical history containing five parameters for the prediction of heart diseases. The authors implemented the proposed model using ML algorithms, such as the K-neighbors classifier, DT classifier, SVM, RF classifier, and LR to predict and classify heart diseases. The datasets containing 14 features from the 100 persons were collected to classify for heart disease and non-heart disease based on the test reports. The K-neighbors classifier performs better compared to other ML algorithms.

Karthick *et al.* [13] implemented a cardiovascular disease risk prediction using ML algorithms. For experimentation purposes, the datasets were collected from the Cleveland heart disease containing 13 selected features from the 303 data instances. The authors implemented the proposed model using six ML algorithms, such as SVM, LR, gaussian Naïve Bayes, LightGBM, XGBoost and RF, to predict the heart disease risk. Out of the available datasets, 80% were used for training the model, and the remaining 20% were used for testing the model and evaluating the model for accuracy using Chi-Square distribution. The RF model performs better compared to other ML models.

Doppala *et al.* [14] developed a hybrid ML algorithm to predict coronary diseases using the feature selection method on the heart dataset. For experimentation purposes, the datasets were collected from the Cleveland heart disease containing 14 selected features from the 303 data instances. The authors implemented the proposed algorithm using machine algorithms, such as Naïve Bayes, DT, LR, SVM, RF, KNN and proposed genetic algorithm (GA) with radial basis function (RBF) to predict CHD. For training, 70% of the datasets were used, and the remaining 30% were used for testing the model. The proposed model GA with RBF performs better than the other ML models.

From the several state-of-the-art works, the prediction of coronary artery heart diseases is in the infancy of the real-time implementation of the model. Here, algorithms need to be improved or upgraded for the betterment of the application. So, this field attracts many eminent and young researchers, showing ample opportunity for the real-time prediction of CHD.

3. METHOD

Explaining in the proposed method, the prediction of CHD is done through two stages such as feature extraction and classification, as shown in Figure 1. Initially, the datasets collected around the Mysore and Mandya regions were pre-processed to normalize, encode, and handle missing values to extract the features using TabNet [15]. During the second stage, the extracted features are processed by concatenating features into a unified feature vector to train the multiclass SVM model [16].

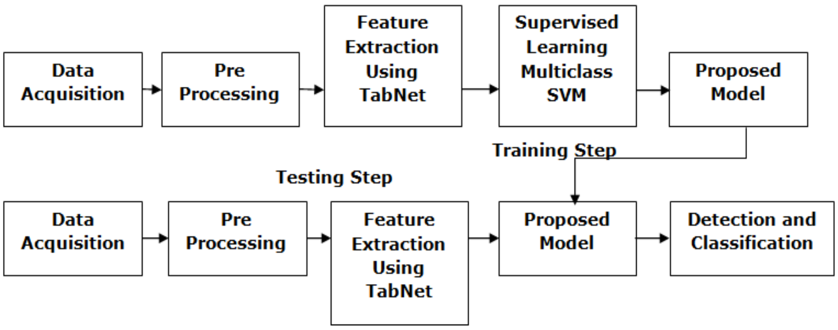

Figure 1. Proposed model for the prediction of CHD

3.1. Dataset

For the experimentation purpose, considering 16 features causing CADs directly or indirectly, such as blood pressure, hyperlipidemia, body mass, sex, age, triglyceride, HDL, LDL, heart rate, creatinine, diagnosis, family history, smoking, diabetes, cholesterol, and glucose are collected in and around the hospitals located in Mysore and Mandya regions, Karnataka, India. A total of 282 datasets containing all 16 features were collected, where 213 datasets were from hospitals in the Mysore region, Karnataka, India and 69 datasets from hospitals in the Mandya region, Karnataka, India. The correlation among the 16 features is interpreted with a coefficient range ranging between -1 to +1, where -1 indicates the strong negative correlation and +1 indicates the strong positive correlation. Figure 2 shows that positive value among the features, which indicates that the features are moving in the same direction.

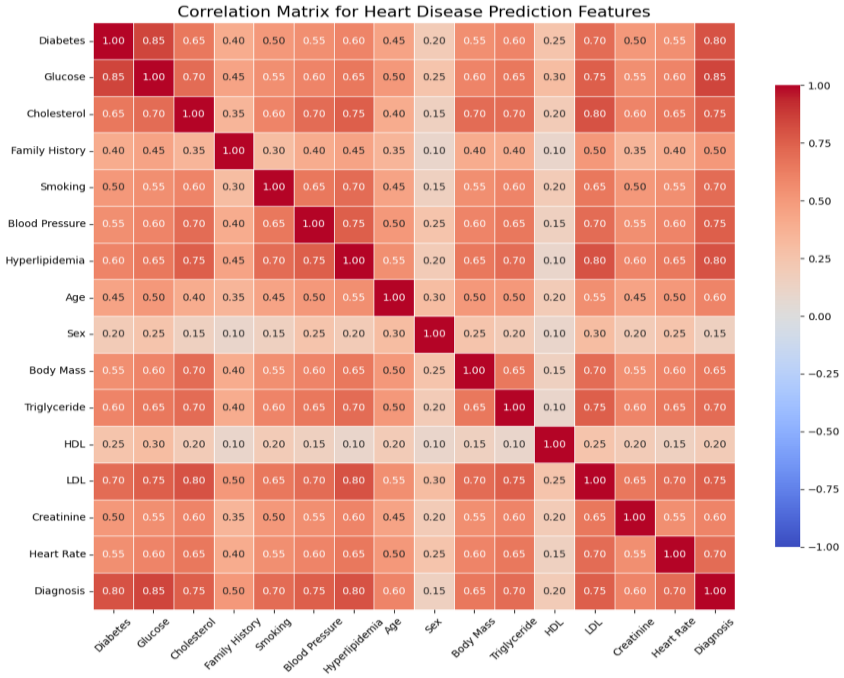

Figure 2. Correlation matrix for the heart disease features

3.2. Pre-processing

The datasets collected are tabular data preprocessed to achieve the model's optimal performance. Before applying to TabNet, the tabular dataset is preprocessed by feature scaling, data cleaning and encoding categorical features. In feature scaling, the normalization method is applied to scale the numerical features from 0 to 1 from the different ranges. The data cleaning method handles the missing values by applying the imputation and deletion [17]. The encoding categorical features method converts the categorical values into binary values by one-hot encoding [18].

3.3. TabNet

TabNet was developed by Google Cloud AI researchers to handle complex tabular data more effectively compared to gradient boost and DT models. TabNet uses sparse attention and a feature transformer mechanism, which helps to focus on the most relevant features for decision by improving interpretability and performance [19]. The feature selection using TabNet is shown in Figure 3, which consists of multi-step sequential operations one after the other. In the initial step, all the pre-processed datasets were given to the model to pass through the feature transformer [20]. The feature transformer consists of a gate linear unit (GLU) block; each GLU block consists of a fully connected (FC) layer, batch normalization (BN), and GLU as shown in (1). To get stability and maintain variance, a normalization of 0.25 is applied after every block.

$$GLU(x) = \sigma(x) \cdot x \tag{1}$$

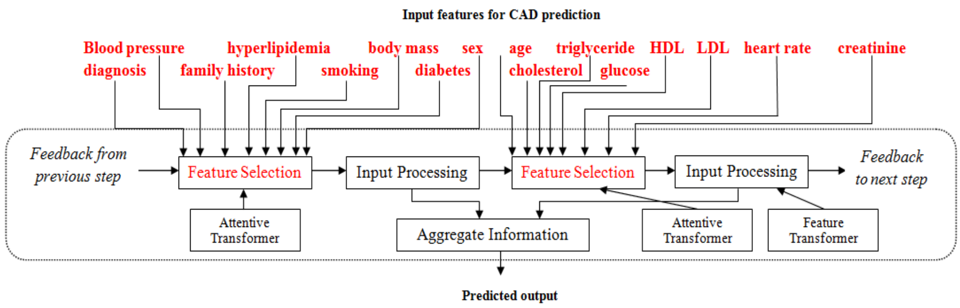

Figure 3. TabNet prediction for feature selection

An attentive transformer consists of a FC, BN, Prior Scales, and Sparsemax layer, which receives data to Prior Scales after passing the FC and BN layer. The aggregation of the feature used till the process step is taken before Prior Scales makes the current decision. Sparse selection of features is done by normalizing the coefficient values [21], which is similar to SoftMax operation as shown in (2).

$$\sum_{i=1}^{n} sparsemax \quad (x_i)_i \quad = \quad 1 \forall x \in \quad R^n \tag{2}$$

The output from the attentive transformer step is then supervised by the attention mask, which helps to identify the selected features. The mask quantifies the importance of aggregate features and analyzes each step, allowing aggregate decisions as given in (3) [22]. As specified in Figure 3, all the 16 selected features were presented to feature selection, which underwent feature transformer and attentive transformer processing before aggregating the decision of features.

$$n_b[i] \quad = \quad \sum_{c=1}^{N_d} ReLU \quad (d_{b,c} \quad [i]) \tag{3}$$

The feature selection process was completed by applying the TabNet model; next, we need to go for the prediction of CHD. Here, the model needs to be trained and tested for better performance and evaluated the model performance using evaluation metrics.

3.4. Multiclass SVM

Combined features are fed to the SVM algorithm for detecting CHD [23]. The SVM model is trained to classify the disease, as shown in Figure 4. In the training phase, the model is trained for each class considering the three classes. Classes such as Class 0: No disease, Class 1: Mild disease and Class 2: Severe disease based on the extracted feature values. Each of these classes will be trained to be distinguished from others, as shown in Figure 4. During the prediction phase, based on the probability score it shows the likelihood of instances belonging to a class with respective classes. Finally, the maximum score is selected as the instance for the prediction of the class [24], [25].

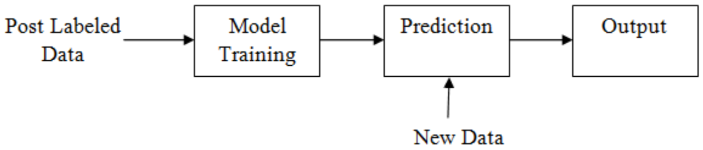

Figure 4. SVM algorithm for the prediction of CHD

4. RESULTS AND DISCUSSION

In this section, we present the simulation results on a Google Colab using Python for the datasets collected in and around the hospitals in Mysore and Mandya regions, Karnataka, India. As specified in the dataset section, here we have collected 282 datasets, of which 130 datasets belong to class 0, 86 to class 1, and the remaining 66 to class 2. Approximately 50% of the available datasets in each class were used to train the model, and the remaining was used to test the model performance. Some datasets were also randomly given, which are not considered in the dataset part. In the first phase, the features are aggregated using the TabNet model, which considers the 16 selected feature values causing CADs directly or indirectly, such as blood pressure, hyperlipidemia, body mass, sex, age, triglyceride, HDL, LDL, heart rate, creatinine, diagnosis, family history, smoking, diabetes, cholesterol, and glucose. During the second phase, extracted features were fed to the multiclass SVM model for the prediction of the classes that belong based on the highest score.

The model's performance is evaluated using evaluation metrics such as precision, recall, F1-score, and accuracy, and the results are indicated in Table 1. Class 0 means the prediction of no CAD diseases shows a result of precision of 93.38%, recall of 90.76%, F1-score 92.05%, and accuracy of 90%. Class 1 indicates the prediction of mild CAD diseases, with 91.86% precision, recall at 89.53%, F1-score at 90.68%, and accuracy at 88.37%. Class 2 indicates the prediction of severe CAD diseases, which shows a precision of 90.90%, recall of 87.20%, F1-score 89.01%, and accuracy of 87.87%. Figure 5 shows the graphical representation of the result class versus evaluation metrics.

Table 1. Performance of model

Class	Precision	Recall	F1-score	Accuracy
0	93.38	90.76	92.05	90
1	91.86	89.53	90.68	88.37
2	90.90	87.20	89.01	87.87

Figure 5. Graphical representation of performance of the model

The proposed model performance is compared with the previous related work carried out by researchers and is shown in Table 2. Predictions of CAD disease-related works carried out by the researchers were very few in number, and even the datasets considered were repository datasets. In our proposed hybrid model, we have worked by creating our own datasets through our own visits collected in and around the hospitals in Mysore and Mandya regions, Karnataka, India. Even the result achieved with a hybrid model, TabNet for feature extraction and multiclass SVM for prediction of the class shown outer performance as shown in Table 2.

Table 2. Algorithm performance comparison with state-of-the-art

State-of-the-art	mAP* (%)
Proposed model	92.05
Karthick, K. *et al.* [13]	89.32
Chang, Victor, *et al.* [12]	87.45

*mAP (mean average precision)

5. CONCLUSION

Heart disease is the leading cause of death in both men and women, affecting the function and structure of the heart. Currently, heart disease is diagnosed using a variety of laboratory tests and imaging studies such as ECG, holter monitoring, echocardiogram, exercise or stress tests, cardiac catheterization, cardiac CT scan, and cardiac MRI scan. These tests require time for physicians to interpret the results and treat the patient. Given the critical nature of the patient’s condition, an accurate diagnosis is essential to save lives within a specified timeframe. We have developed a hybrid model based on TabNet and Multiclass SVM to address this. We collected our datasets for experimentation from hospitals in the Mysore and Mandya regions of Karnataka, India. The datasets consist of 16 features that have been pre-processed to normalize, encode, and handle missing values. TabNet is used to extract aggregate features, and the multiclass SVM model is trained to classify the disease based on the classes. The performance of the proposed hybrid model was evaluated using various metrics such as accuracy, recall, precision, and F1-score.

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AUTHOR CONTRIBUTIONS STATEMENT

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Niveditha Honnemadu Rudreshgowda	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Balakrishna Kempegowda	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		
AnithaSammilan	✓		✓	✓			✓			✓	✓		✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing -**O**riginal Draft
E : Writing - Review &**E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors have no conflicts of interest to declare relevant to this article's content.

DATA AVAILABILITY

The data that support the findings of this study are available on request from the corresponding author, [BK]. The data, which contain information that could compromise the privacy of research participants, are not publicly available due to certain restrictions.

REFERENCES

[1] F. Bessière, B. Mondésert, M.-A. Chaix, and P. Khairy, "Arrhythmias in adults with congenital heart disease and heart failure," *Heart Rhythm O2*, vol. 2, no. 6, pp. 744–753, Dec. 2021, doi: 10.1016/j.hroo.2021.10.005.

[2] B. K and D. V, "A review on animal detection and classification using computer vision techniques: scope for future enhancement to application," in *2023 International Conference on Recent Trends in Electronics and Communication (ICRTEC)*, Feb. 2023, pp. 1–6, doi: 10.1109/ICRTEC56977.2023.10111888.

[3] Balakrishna K. and M. Rao, "Tomato plant leaves disease classification using KNN and PNN," *International Journal of Computer Vision and Image Processing*, vol. 9, no. 1, pp. 51–63, Jan. 2019, doi: 10.4018/IJCVIP.2019010104.

[4] A. Alam and A. Mohanty, "Predicting students' performance employing educational data mining techniques, machine learning, and learning analytics," in *Communications in Computer and Information Science*, vol. 1893 CCIS, 2023, pp. 166–177.

[5] V. Dhanushree and K. Balakrishna, "Detection of wildlife animals based on transfer learning using ResNet algorithm," P*roceedings of the First Artificial Intelligence Summit on Smart Sustainable Society*,2024, pp. 173-181, doi: 10.1007/978-981-97-7592-7_14.

[6] Balakrishna K., "Fusion approach-based horticulture plant diseases identification using image processing," in *Applications of Advanced Machine Intelligence in Computer Vision and Object Recognition: Emerging Research and Opportunities*, 2020, pp. 119–132.

[7] M. Gordan *et al.*, "State-of-the-art review on advancements of data mining in structural health monitoring," *Measurement*, vol. 193, p. 110939, Apr. 2022, doi: 10.1016/j.measurement.2022.110939.

[8] P. Sunhare, R. R. Chowdhary, and M. K. Chattopadhyay, "Internet of things and data mining: an application oriented survey," *Journal of King Saud University - Computer and Information Sciences*, vol. 34, no. 6, pp. 3569–3590, Jun. 2022, doi: 10.1016/j.jksuci.2020.07.002.

[9] K. M. Mohi Uddin, R. Ripa, N. Yeasmin, N. Biswas, and S. K. Dey, "Machine learning-based approach to the diagnosis of cardiovascular vascular disease using a combined dataset," *Intelligence-Based Medicine*, vol. 7, p. 100100, 2023, doi: 10.1016/j.ibmed.2023.100100.

[10] M. M. Ali, B. K. Paul, K. Ahmed, F. M. Bui, J. M. W. Quinn, and M. A. Moni, "Heart disease prediction using supervised machine learning algorithms: Performance analysis and comparison," *Computers in Biology and Medicine*, vol. 136, p. 104672, Sep. 2021, doi: 10.1016/j.compbiomed.2021.104672.

[11] X. Y. Gao, A. Amin Ali, H. S. Hassan, and E. M. Anwar, "Improving the accuracy for analyzing heart diseases prediction based on the ensemble method," *Complexity*, vol. 2021, 2021, doi: 10.1155/2021/6663455.

[12] V. Chang, V. R. Bhavani, A. Q. Xu, and M. Hossain, "An artificial intelligence model for heart disease detection using machine learning algorithms," *Healthcare Analytics*, vol. 2, p. 100016, Nov. 2022, doi: 10.1016/j.health.2022.100016.

[13] K. Karthick, S. K. Aruna, R. Samikannu, R. Kuppusamy, Y. Teekaraman, and A. R. Thelkar, "Implementation of a heart disease risk prediction model using machine learning," *Computational and Mathematical Methods in Medicine*, vol. 2022, pp. 1–14, May 2022, doi: 10.1155/2022/6517716.

[14] B. P. Doppala, D. Bhattacharyya, M. Chakkravarthy, and T. Kim, "A hybrid machine learning approach to identify coronary diseases using feature selection mechanism on heart disease dataset," *Distributed and Parallel Databases*, vol. 41, no. 1–2, pp. 1–20, Mar. 2021, doi: 10.1007/s10619-021-07329-y.
[15] K. McDonnell, F. Murphy, B. Sheehan, L. Masello, and G. Castignani, "Deep learning in insurance: accuracy and model interpretability using TabNet," *Expert Systems with Applications*, vol. 217, p. 119543, May 2023, doi: 10.1016/j.eswa.2023.119543.
[16] A. M. Elsayad, A. M. Nassef, and M. Al-Dhaifallah, "Bayesian optimization of multiclass SVM for efficient diagnosis of erythemato-squamous diseases," *Biomedical Signal Processing and Control*, vol. 71, p. 103223, Jan. 2022, doi: 10.1016/j.bspc.2021.103223.
[17] K. Balakrishna, F. Mohammed, C. R. Ullas, C. M. Hema, and S. K. Sonakshi, "Application of IoT and machine learning in crop protection against animal intrusion," *Global Transitions Proceedings*, vol. 2, no. 2, pp. 169–174, Nov. 2021, doi: 10.1016/j.gltp.2021.08.061.
[18] K. Balakrishna and N. G. Sandesh, "Design of dynamic induction charging vehicle for glimpse of future: cutting down the need for high-capacity batteries and charging stations," in *Lecture Notes in Electrical Engineering*, vol. 752 LNEE, 2021, pp. 197–204.
[19] C. Shah, Q. Du, and Y. Xu, "Enhanced TabNet: attentive interpretable tabular learning for hyperspectral image classification," *Remote Sensing*, vol. 14, no. 3, p. 716, Feb. 2022, doi: 10.3390/rs14030716.
[20] C. Yu, Y. Jin, Q. Xing, Y. Zhang, S. Guo, and S. Meng, "Advanced user credit risk prediction model using LightGBM, XGBoost and Tabnet with SMOTEENN," in *2024 IEEE 6th International Conference on Power, Intelligent Computing and Systems (ICPICS)*, Jul. 2024, pp. 876–883, doi: 10.1109/ICPICS62053.2024.10796247.
[21] Y. Chen, H. Li, H. Dou, H. Wen, and Y. Dong, "Prediction and visual analysis of food safety risk based on TabNet-GRA," *Foods*, vol. 12, no. 16, p. 3113, Aug. 2023, doi: 10.3390/foods12163113.
[22] L. P. Joseph, E. A. Joseph, and R. Prasad, "Explainable diabetes classification using hybrid Bayesian-optimized TabNet architecture," *Computers in Biology and Medicine*, vol. 151, p. 106178, Dec. 2022, doi: 10.1016/j.compbiomed.2022.106178.
[23] S. Panigrahi and *et al.*, "An optimal hybrid multiclass SVM for plant leaf disease detection using spatial fuzzy C-means model," *Expert Systems with Applications*, 2020, [Online]. Available: https://www.sciencedirect.com/science/article/abs/pii/S0957417422020073.
[24] T. Gao and H. Chen, "Multicycle disassembly-based decomposition algorithm to train multiclass support vector machines," *Pattern Recognition*, vol. 140, p. 109479, Aug. 2023, doi: 10.1016/j.patcog.2023.109479.
[25] H. R. Niveditha, K. Balakrishna, and S. Anitha, "Machine learning-based cardiovascular heart disease detection: a review with future scope," *Lecture Notes in Electrical Engineering*, vol. 1259 LNEE, pp. 125–135, 2024, doi: 10.1007/978-981-97-7592-7_10.

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