HEART DISEASE PREDICTION USING TREE STRUCTURED PARZEN ESTIMATOR OPTIMIZATION

Abstract— Heart disease is the range of conditions which affects the heart such as heart abnormalities, coronary artery disease, arrhythmias, heart rhythm problems, heart defects present at birth among others. Electrocardiography is the diagnostic tool used to check activities of the heart. While the ECG provides valuable data about the heart rhythm, also the electrical conduction system, it cannot predict heart diseases. However, it is the essential part of detecting various heart conditions and assessing overall health of the heart. TPE is the Bayesian optimization algorithm which is commonly used for tuning the hyperparameter in the models. It's particularly efficient for hyperparameter optimization of many algorithms. TPE builds the probabilistic model of objective function and also it is used to select the most promising hyperparameters for the next iteration. By evaluating and updating the model, TPE efficiently searches the hyperparameter space to find a combination which maximizes or minimizes the objective function. CNNs are a class of neural networks, mainly used for the recognition of images and also vision tasks of the computers. It consists of various layers of the filters that follow the pooling layer and also the fully connected layer. CNNs excel at learning spatial hierarchies of the features from images and make them powerful tools for the tasks like classification of images, detection of objects, and also the partition. This approach mainly aims to automate the process of the hyperparameter tuning that allows efficiency and to find the configuration that gains the best performance for the CNN-based image processing task. By leveraging TPE optimization it achieves the best accuracy of 87.3%.

Keywords—Heart disease, ECG, TPE, CNN, optimization,classification

I. INTRODUCTION

The Heart disease also called cardiovascular disease (CVD) which encompasses a wide range of categories that affects the heart and also the blood vessels. Coronary artery disease arises when narrowing of the blood vessels or blockage of the blood vessels. It can also lead to chest pain, heart attack, or even stroke. Arrhythmia can lead to complications like faint, stroke, or also sudden cardiac arrest. Heart valve problem occurs when valves in the heart do not open or close properly that causes the issues with blood flow. This leads to the main symptoms like chest pain, fatigue and shortness of breath. Regular health check ups are important for the earlier detection. The electrocardiogram is the fundamental tool in cardiology that is assessing the electrical rate of the heart. The impulse causes the heart muscle to contract and relaxes the blood through the circulatory system. By recording the electrical signals, ECG provides valuable data. Electrodes are placed in specific locations for detecting the electrical activities of the heart. The standard ECG includes multiple leads each representing the electrical activity of the heart. Most common configuration is 12-lead ECG, which provides a comprehensive assessment of the heart from different angles. The ECG waveform consists of several components like .P wave-Represents the atrial depolarization and the electrical impulse that triggers atrial contraction. QRS complex that reflects the ventricular depolarization and the electrical activity is associated with ventricular contraction. T-wave denotes the ventricular repolarization. ST segment indicates the time between depolarization and also repolarization. Optimization in the heart disease prediction is crucial for enhancing early detection, personalized medicine, resource allocation, accuracy, risk stratification, preventive interventions, and also the population health management. This ensures the efficient allocation of healthcare resources with high-risk individuals that receive appropriate screening and also the interventions while minimizing unnecessary procedures for the low-risk individuals. Optimization also enables the development of personalized prediction models that consider individual risk factors, genetics, lifestyle, and medical history, leading to tailored interventions and even improved outcomes. By targeting the modifiable risk factors with the preventive interventions like lifestyle modifications and medication, the optimization helps to reduce the incidence of heart disease. Optimization facilitates population-level risk assessment and its management strategies, allows for the implementation of the targeted public health initiatives to mitigate the overall burden of heart disease. After optimization the classification remains pivotal in heart disease prediction for many reasons.Firstly, it refines the risk stratification by categorizing individuals into distinct risk groups based on the predicted probabilities of developing the heart disease. This precision enables the healthcare providers to prioritize interventions effectively while focusing on the resources where they are needed. Secondly the classification provides actionable insights for the clinical decision-making and guiding treatment choices, disease monitoring, and intervention adjustments based on changing risk profiles.In essence, classification complements optimization that empowering healthcare providers to deliver personalized, evidence-based care and improve outcomes for individuals at risk of heart disease..

II. LITERATURE REVIEW

The Myocardial infarction MI is also called the heart attack which causes damage to the muscles of heart and also it leads to death. The electrocardiogram and blood test are used for the diagnosis of the acute Myocardial infarction. When increasing the blood enzyme levels several times should be passed. The delay of time lag leads to the diagnosis of disease. The diagnosis of the disease is very important. Hence the diagnosis might be important for detection in ECG for the MI. the deep learning model with CNN algorithm for the end to end structures in the standard 12-lead of ECG signals used for diagnosis of the MI. The CNN model gives accuracy and also sensitivity about 99%. This model have potential for providing the high performance of the detection of MI which is used for various technologies in Ulas Baran Baloglua et al.,[1]

The classification of heart condition using ECG and automated diagnosis using advanced methodology have been proposed for the rising death rate from CVD. The ECG from the dataset is integrated with the multi model framework that is refined from the Gradient Descent and used to classify the K-means algorithm. The CNN algorithm is used for detecting the anamolies. This study achieves the accuracy of 98% and specificity, sensitivity show massive improvements. The cardiovascular disease type is detected in Ninni Singh et al.,[2] by using the confusion matrix.

The advancement in the field of medicine which increases the demand of prediction of disease also with the system classification. There are various disease classification techniques using machine learning that face severe issues. The (WbGAS) Wolf based Generative Adversarial System is an optimized framework used for finding and also specifying heart disease. The model is trained using WbGAS for predicting the normal and also the abnormal signals. The heart disease type is specified using the trained features. The performance is determined by accuracy, precision, recall, specificity. The outcomes are compared with the existing machine learning approaches in P. Satyanarayana Goud et al.,[3]

To develop the interactive classifier with aided deep learning algorithm for assisting the cardiologist with arrhythmia heart disease classification shows threatening conditions which leads to the heart related complications. In this paper Marwa Fradi et al.,[4] the algorithm is used for the classification of patients ECG signals into classes which is based on the ANSI-AAMI standard. This is a multistage technique. The stage first combines R-R with the less pass and its filter is applied. The stage second is CNN which is based on connected layers of architecture with various optimizers. The different databases are used for the validation purposes. The accuracy in classification is 99.37% for training ,

99.15% for validation and 99.31 for testing set. For MIT-BIH database results 99.5%.

Among many chronic disease in all over the world, Cardiovascular disease are the widely spread disease. CVD represent the main cause for mortality and morbidity. In this work Hossam Magdy Balaha et al.,[5] the detection of heart disease with the voice recordings are given. It contains multiple layers like Feature Extraction layer responsible for the graphical and numerical features, segmentation layer based on segmentation with duration of variables and also directions, statistics and export layer, optimization and learning layer. The proposed system consists of 11 datasets and 14416 features.

This paper Dinesh Kumar Atal et al., [6] states the automatic classification of arrhythmia by usage of the optimization with convolutional neural networks. The Bat-Rider is developed using the Rider Optimization algorithm and multiple objective bat algorithms. At the first gabor and wave features were extracted with the ECG signals. The signals were provided with a BaROA based classifier which identifies the conditions of individuals as Arrhythmia. The methods were analyzed by using the MIT-BIH database and also the analysis of the performance with evalution parameters like accuracy, sensitivity and specificity which is 93.19%, 93.98% and 95%.

In this paper the new computational model which is used on swarm optimization and CNN is used for the five class classification of MITDB dataset. The main goal of PSO is for optimizing the hyper parameter which define CNN layered architecture that increases accuracy and decreases categorical cross entropy Error. This paper found satisfactory layer architecture with 17.68 hours which obtained accuracy of 97% , 98% . The result demonstrates the model Fredy Santander Banos et al.,[7] was reliable and it represents an innovative approach for allowing dispersing and with manual selection in cnn.

The deep learning algorithm was used as feature extractors. The CNN algorithm generate a rich features for the different scale. The main aim Xianbin Zhang et al.,[8] is to improve the performance classification of AF and also some short ECG segment. The fused feature is trained and it is tested in SVM. The F1 Score shows method out performance and it is not same for CNN without the feature fusion with an average of F1 score is 84.3%.

The main objective is developing new techniques and testing the classifications for improving heart disease detection. Hybrid optimization is used for this research. The data are taken and preprocessed. Then data is subjected to feature fusion so that it is carried by coefficient and overlapping the coefficient which is enabled for deep belief network. This principle can be effectively trained by multiple

Sonam Palden Barfungpa et al.,[14] propose the HD system with deep dense networks for the prediction of heart disease at the earliest stage. Initially this proposed system performs data acquisition. This was in the Python platform and it evaluated the performance in the terms of different performance metrics using the heart disease dataset. The maximum accuracy is 99.57% in the proposed scheme.

This paper Md Mamun Ali et al.,[15] aims to identify the classifier with accuracy for the treatment purposes. The features were categorized with the score that helps in finding the huge prediction of heart diseases. This heart disease dataset was gathered based on the decision tree , KNN, random forest which achieved the accuracy of 100%.

classifiers which helps to improve the accuracy. The result is combined which helps to produce final

III. PROPOSED METHODOLOGY

result. Moreover the proposed work has a low computation time and hence it improves the efficiency in R. Jayasudha et al.,[9]

This work Anila Soman et al.,[10] develop an effective approach which is as a Chameleon Sparrow Search Algorithm that trains the deep CNN by using the ECG signals for classifying the arrhythmia. The features from auto-regressive, DWT, VMD, EMD are extracted. The CsSA is proposed by the integration of the Sparrow Search Algorithm and also the Chameleon Swarm Algorithm. It produces an accuracy of 0.947 and sensitivity of 0.929.

CNN has become most commonly used for the medical decision system for predicting and also for diagnosing different diseases. The proposed Ali A. Samir et al.,[11] CNN-jSO is compared to other algorithms and it resulted to be better among them. The CNN-jSO has training accuracy of 97.76% and the testing accuracy of 94.12% .

The main aim Ankita Tyagi et al.,[12] is to design a hybrid CNN by use of an GOA which is to divide the different diseases from ECG signals and also the heartbeats. The proposed heartbeat classification model was verified with the database and accuracy is to be 99.58% where accurate classified heartbeat is 86005 and the wrongly classified beats are 0.42 % error rate.

This paper M. Karthiga et al.,[13] aid the physician in an early and also the accurate analysis of the heart disease. The work has a proposal of the hybrid Grey Wolf Optimizer and Artificial bee colony algorithms which continue the originality of the human strategy for the maintenance of the exploration capability.

1. DATASET SUMMARY

Dataset used in research contains heartbeat signals extracted from two primary sources: the MIT-BIH Dataset and also the PTB ECG Database. The MIT BIH Dataset includes a total of 109,446 samples divided into five categories: Normal beats, Unknown beats, Supraventricular ectopic, Fusion and Ventricular ectopic beats. Table 1 deals with the overview of the dataset. The signals in this dataset were recorded at a frequency of 125Hz, with the data sourced from Physionet's MIT-BIH Arrhythmia collection. The class distribution is approximately 60,000 samples for 'N', 20,000 for 'S', 15,000 for 'V', 5,000 for 'F', and 9,000 for 'Q'.

On the other hand, the PTB Diagnostic ECG Database contains 14,552 samples across two categories—Normal and Abnormal heartbeats—also sampled at 125Hz. This dataset includes around 11,000 samples for 'Normal' and 3,500 for 'Abnormal'. Table 2 is the Class distribution of the MIT-BIH Dataset and Table 3 is the Class distribution of the PTB Dataset.

Table 1 Summary of Dataset

Dataset	Number of samples	Categories	Sampling frequency
MIT-BIH Arrhythmia Dataset	109,446	N, S, V, F, Q (5 classes)	125Hz

PTB Diagnostic ECG Database	14,552	Normal, Abnormal (2 classes)	125Hz

Table 2 Class distribution in the MIT-BIH Dataset

MIT-BIH Dataset Class Distribution	Total Samples
N (Normal)	60,000
S (Supraventricular)	20,000
V (Ventricular)	15,000
F (Fusion)	5,000
Q (Unknown)	9,000

Table 3 Class distribution in the PTB Diagnostic Dataset

PTB Diagnostic Dataset Class Distribution	Number of Samples
Normal	11,000
Abnormal	3,500

2. PREPROCESSING OF DATA

Several techniques are used to increase robustness of prediction models. Shearing transformations are used to alter the image perspective, helping the model recognize features from different angles. Random zooming of up to 20% ensures the model can detect objects at various scales. Horizontal flipping is applied to augment the dataset by introducing left-right symmetry. Any missing pixels caused by transformations are filled using the nearest neighboring pixel values to avoid empty spaces in the image. Additionally, it is partitioned into training sets and also the validation sets allowing the model to be validated on unseen data during training. All images are resized to 48x48 pixels for input consistency across the CNN model, while a categorical class mode is used for the multi class classification task.

3. CNN WITH TPE OPTIMIZATION

In CNN with TPE optimization, hyperparameters like size of the batches, layers, filters, kernel size, dense units, and learning rate are automatically fine tuned using the TPE. TPE is used for optimal hyperparameters by evaluating different combinations across trials, leading to improved accuracy and validation performance. This results in better model generalization and faster convergence. The model is thus trained efficiently and effectively, with fewer manual interventions.

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p(θ) = TPE(L_val, N_trails) eq (1)

In equation 1, θ is the Set of hyperparameters, f(X_train; θ)is the CNN model parameterized by θ, trained on the training data X_train, L_val is the Validation loss function ,p(θ) is the Probability distribution over the hyperparameters and TPE: Tree-structured Parzen Estimator that tunes θ based on a given number of trials N_trials, optimizing for lower L_val

4. CNN WITHOUT TPE OPTIMIZATION

In CNN without TPE optimization, the model is trained with manually selected, fixed hyperparameters. Without the systematic tuning provided by TPE, the hyperparameters may not be optimal, leading to potentially lower accuracy and higher validation loss. The model might take longer to converge or fail to capture important patterns in the data. This could result in overfitting, or underfitting. Overall, the training may be less successful and less effective.

��������=minimize L(f(X_train; θ_fixed)) eq (2)

In equation 3.2, θ_fixed is the Fixed hyperparameters manually chosen before training and L(f(X_train; θ_fixed)) is the Validation loss for the CNN model with fixed hyperparameters, evaluated after training.

1. 5 .TREE STRUCTURED PARZEN ESTIMATOR

TPE TPE stands for "Tree-structured Parzen Estimator. It is an algorithm used for the hyperparameter optimization in models. The goal of the TPE is efficiently searching through the high dimensional hyperparameter to find a set of hyperparameters that optimize a given objective function. TPE algorithm is based on Bayesian optimization principles and operates iteratively. It maintains two probability density functions (PDFs) for each hyperparameter: one for "good" configurations and one for "bad" configurations. These PDFs are updated based on the performance of evaluated configurations.TPE balances exploration and exploitation by sampling new hyperparameter configurations more frequently from the “good” PDF but occasionally sampling

from the “bad” PDF to explore potentially better configurations. It selects the next hyperparameter configuration to evaluate based on the trade-off between exploration and exploitation, typically choosing configurations with higher expected improvement over the current best configuration. By iteratively evaluating and updating hyperparameter configurations, TPE goals for efficiently exploring hyperparameters space and also finding configurations which lead to better model performance. It is implemented in libraries like hyperopt, which provides a convenient interface for hyperparameter optimization using TPE and other algorithms. Figure 1 shows the implementation of TPE.

```python
study = optuna.create_study(direction='maximize', sampler=optuna.samplers.TPESampler())
study.optimize(objective, n_trials=50)

best_trial = study.best_trial


print(f"Best trial parameters: {best_trial.params}")
print(f"Best trial value: {best_trial.value}")

best_hp = best_trial.params
final_model = create_model(best_hp)
final_model.fit(
    train_ds,
    validation_data=val_ds,
    epochs=best_hp['epochs'],
    batch_size=best_hp['batch_size']
)
```

Figure 1 Implementation of TPE

ALGORITHM

Step 1: Define the Search Space for Hyperparameters. Begin by establishing the range or distribution for each hyperparameter. For instance, you might set a batch size range between 16 and 64.Generate an initial set of hyperparameter configurations either randomly or through advanced sampling techniques like Latin hypercube sampling.

Step 2: In TPE, two probability density functions (PDFs) are maintained: one for "good" configurations and one for "bad" configurations. The "good" configurations are those that yield better performance than the median value, while the "bad" configurations result in worse performance. Kernel Density Estimation (KDE) is used to estimate these PDFs:

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In Equation 3, F represents the kernel function, r is the bandwidth parameter, are the observed configurations, and n denotes the number of observations.

Step 3: Calculate the objective function which typically measures the result of a model trained with the given hyperparameters. This could be accuracy loss or any other metric relevant to the specific problem.

Step 4: Update the PDFs based on the evaluated configurations. For “good” configurations update the PDF using KDE with configurations that performed better than the median. For “bad” configurations update the PDF using KDE with configurations that performed worse than the median.

Step 5: Sample new hyperparameter configurations from the PDFs. To balance exploration and exploitation, sample more frequently from the “good” PDF but occasionally sample from the “bad” PDF.

Step 6: Select the upcoming configuration which is used for evaluating based on expected improvement over current best configuration. Compute the expected improvement for each sampled configuration which quantifies how much better the new configuration is expected to perform compared to the current best one. Select the configuration with the highest expected improvement for evaluation

Step 7: Continue the process of evaluating configurations, updating PDFs, and sampling new configurations until stopping criteria is satisfied. It could be a large number of evaluations or achieving well desired performance level

2. 6. CONVOLUTIONAL NEURAL NETWORK

Convolutional Layers: CNNs consist of multiple layers, typically including the convolutional layer. This layer applies the operations to incoming data, which helps to gather varieties of features from the images.

Pooling Layers: CNNs often include the pooling layers. Pooling layers are used for downsampling that reduces the dimensions of the data while preserving necessary features.

Fully Connected Layers: CNNs contain single or multiple fully connected layers. These layers enable each neuron in the first layer to another neuron in the second layer then allows them to learn about the features and then make decisions from the extracted features.

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eq(4) where tp stands for true positive, tn stands for true negative, fp stands for false positive, fn stands for false negative. Accuracy for this model is 85% for CNN and 96% for CNN with TPE.

Precision focuses on accuracy of positive prediction, reflecting the proportion of actual


```
x = Flatten()(base_model.output)
x = Dense(512, activation='relu')(x)
x = Dropout(0.5)(x)
predictions = Dense(num_classes, activation='softmax')(x)

model = Model(inputs=base_model.input, outputs=predictions)

model.compile(optimizer=Adam(learning_rate=0.001),
              loss='categorical_crossentropy',
              metrics=['accuracy'])
history = model.fit(
    train_generator,
    steps_per_epoch=len(train_generator),
    epochs=5,
    validation_data=test_generator,
    validation_steps=len(test_generator)
)
test_loss, test_acc = model.evaluate(test_generator, steps=len(test_generator))
print(f'Test accuracy: {test_acc * 100:.2f}%')
```

Figure 2 Implementation of CNN

Training: CNNs used to be trained in backpropagation and also some optimization techniques like gradient descent. During training, the network learns to adjust parameters of layers to reduce a defined loss function, by comparing the resulting outputs to the correct labels.

Transfer Learning: CNNs are often used for transferring the learning on huge datasets that are fine-tuned on certain tasks or datasets with limited labeled data. This approach helps leverage the knowledge gained from training on large datasets and achieve better performance on smaller datasets. Figure 2 shows the implementation of CNN.

IV. EXPERIMENTAL RESULTS

Optimization algorithms are used for finding the hyperparameter for a model. In Figure 5, X axis represents the different performance measure used in the proposed work, Y axis represents the score for each algorithm. CNNs accuracy is 85% and TPE with CNN accuracy is 96%. Figure 3 denotes the confusion matrix for CNN and Figure 4 visualize the confusion matrix for CNN with TPE that are used for evaluating the classification models and their performance which gives a visual representation of the models performance by presenting counts of the true positives, false positives, true negatives and false negatives, aiding in assessing accuracy and error rates of the classification predictions. Table 4.1 deals with the hyperparameter optimization results.

Accuracy gives the percentage of correct forecast out of all forecasts. It shows how often the model's predictions are correct overall. The formula for calculating accuracy is shown in equation 4.

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positives in positive predictions.The formula for calculating precision is shown in the equation 5. The precision for this model is 49% for CNN and 46% for CNN with TPE.

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Recall calculates the percentage of real positives that the model predicted. High Recall means that most positive cases were identified. The formula for calculating recall is shown in the equation 6. The recall for this model is 51% for CNN and 49% for CNN with TPE.

������������ = ����/���� + ���� eq (6)

The F1 score offers equilibrum with the precision and recall by taking their harmonic mean. Equation 7 displays the formula used to determine F1 score. The F1-score for this model is 50% for CNN and 47% for CNN with TPE.

��1 −���������� = 2 ∗ (�� ∗ ��)/(�� + ��) eq (7)

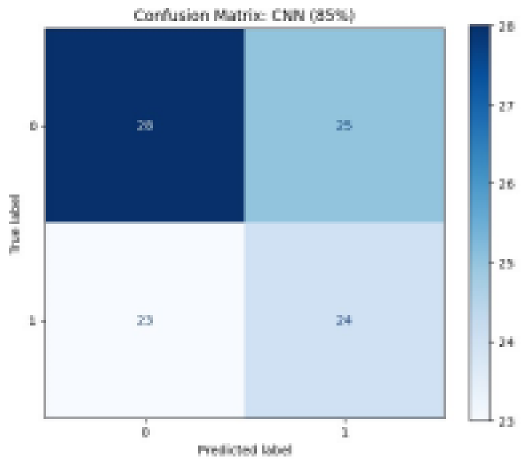

FIGURE 3 CONFUSION MATRIX FOR CNN

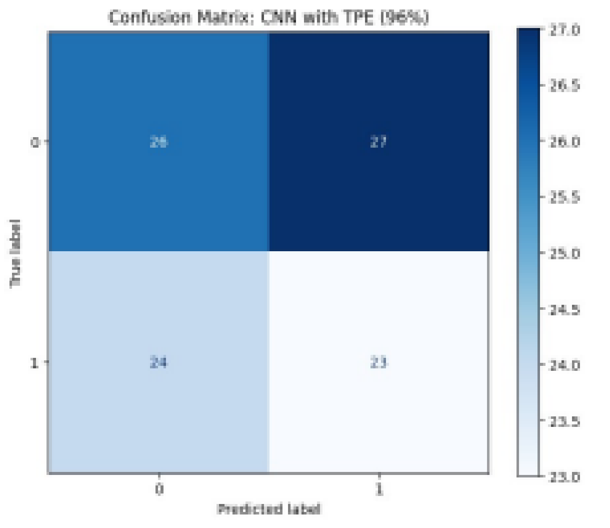

FIGURE 4 CONFUSION MATRIX FOR CNN WITH TPE

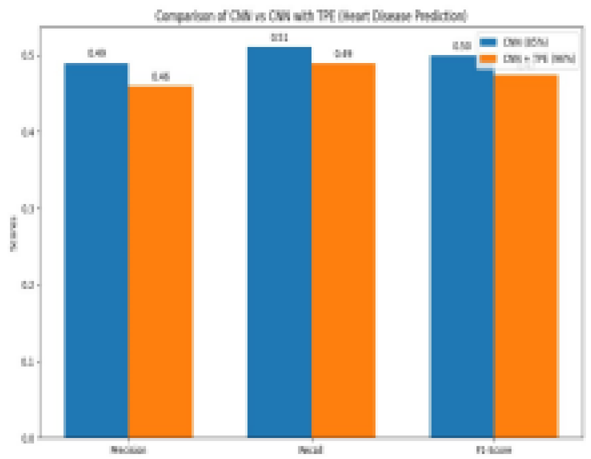

FIGURE 5 COMPARISON OF CNN AND CNN WITH TPE

The previous research has produced a number of optimization-enabled deep convolutional neural networks (DCNNs) with the usage of ECG signals to classify the arrhythmias. CNN with feature extraction concentrating on QRS, P, and T waves, optimised with the SSA and also the CSA algorithm, obtained an accuracy of 94.7%, but a DCNN optimised with the Bat-Rider Optimisation Algorithm (BaROA) obtained an accuracy of 93.19%. The Artificial Bee Colony and Grey Wolf Optimiser were used in a hybrid optimised CNN for remote sensor-based ECG monitoring, with accuracy values of 88.63%, 90.43%, and 92.03%. By contrast, my model, "Heart Disease Prediction using Tree structured Parzen Estimator Optimisation," achieves an accuracy of 85% without CNN and 96% with CNN by employing a CNN optimized with Tree-structured Parzen Estimator (TPE).

TABLE 4 Hyperparameter Optimization Results for Training

Batch size	Number of layers	Filters	Learning Rate	Training accuracy	Training loss
59	1	25	0.000838	85.12 %	0.424
38	1	128	0.004267	88.32 %	0.319
38	2	38,96	0.001376	89.45 %	0.295
33	2	81, 124	0.000141	91.08 %	0.267
56	2	65,35	0.001395	93.22 %	0.241

In table 4, the results of training CNN models with different hyperparameter configurations for heart disease prediction. It includes the size of batches, layers, filters, learning rate, alongside their corresponding training accuracy and loss. As the number of layers, filters, and batch sizes vary, the models show a steady improvement in accuracy, ranging from 85.12% to 93.22%, and a reduction in training loss from 0.424 to 0.241. Lower learning rates and increased complexity in model architecture appear to yield better performance.

The table 5,summarizes the validation performance of CNN models with different hyperparameter settings for heart disease prediction. It highlights the batch size, number of layers, filters, and learning rates, along with their associated validation accuracy and loss. The results show that as the complexity of the model increases, particularly with more layers and filters, validation accuracy improves, reaching a high of 96.00%. Concurrently, the validation loss decreases, with the lowest being 0.250. The choice of learning rate and filter size has a noticeable impact on both accuracy and loss.

TABLE 5 Hyperparameter Optimization Results for validation

Batch	Num	Filters	Lear	Validat	Validati

size	ber of layers		ning Rate	ion accuracy	on loss
59	1	25	0.000838	82.64%	0.512
38	1	128	0.004267	84.27%	0.457
38	2	38,96	0.001376	96.00%	0.250
33	2	81, 124	0.000141	88.17%	0.354
56	2	65,35	0.001395	89.35%	0.329

V. CONCLUSION

The successful implementation of the Convolutional Neural Networks (CNN) alongside the Tree-structured Parzen Estimator (TPE) algorithm has demonstrated significant promise in heart disease prediction, which achieve the best accuracy of 96%. Foundational work paves the way for future research aimed at enhancing predictive performance through ensemble learning techniques. By combining multiple CNN models trained on varied subsets of the dataset or employing diverse architectural designs, the research aims to leverage the strengths of different models, thereby improving overall classification accuracy and robustness. Such an approach not only has the potential to acquire a broader variety of the feature but it mitigates limitations of individual models, ultimately contributing to more reliable heart disease prediction systems.

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