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A Hybrid Optimized Framework for The Classification and Detection of Cardiac Diseases

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Abstract- The research study ventures into heart signal evaluation and diagnosis machine learning using Vision Transformer (ViT) as the main computation building block. In his work Vazifecas constructs a one- dimensional signal for separating P, QRS, and T segments of heart electrical waves from ECG signals. Staking Ensemble enhances The Cardiovascular ECG Images dataset robustness levels. A Whale- Optimization performs model diagnosis of heart disease in the optimization process of heart signals.

Keywords: Cardiovascular Disease, Convolutional Neural Network (CNN), vision transformer (VIT), Multi-Layer Perceptron (MLP), Whole Optimization Algorithm (WOA).

I. INTRODUCTION

Cardiac diseases and cardiovascular disease are enormous worldwide medical diseases that result in yearly patient deaths in hundreds according to experienced medical professionals. Experienced healthcare doctors ought to diagnose at initial stages of diagnosis in an attempt to give good disease treatment outcomes as early diagnosis of the disease constitutes correct disease classification. Diagnostic errors are created with conservative use of electrocardiogram (ECG) equipment. Individual is utilized by medical doctors to interpret and read heart electrical signatures in efforts to determine heart problems because the diagnostic tool in question is non-specific. ECG information data is the underlying assumption that is applied by physicians in patients' cardiovascular state assessment. ECG machines are employed by physicians in attempting to diagnose cardiovascular structural abnormalities and arrhythmic activity with the capacity to recognize tissue ischemic characteristics.[1]Successful diagnosis is acute observation of electrocardiogram (ECG) when viewed in its waveform along with all the arrhythmias that are viewable through ECG therapy.[2]Physicians employ the 12-lead electrocardiogram (ECG) extensively as their standard diagnostic tool in the application of investigating heart function along with the identification of heart structure abnormalities and conducting system abnormalities. Medical image interpretation continues uninterrupted with deep learning models and computer vision frameworks by image analysis processes. Medical entities benefit since diagnostic CNNs offer low- cost affordable solutions that enable timely bookings of output.

[3] Machine learning platforms are used by healthcare professionals in pattern recognition for fewer cardiovascular diseases in the world at earlier stages as well as in forecasting. [5] Accurate arrhythmia detection is crucial in healthcare. [6] Vision Transformer Model divides input images and allocates sequential token features to every segment. Components utilized as inputs, and worked at the interaction point of feedforward neural networks and self-attention layers, are presented to the system from the initial step itself. ResNet-50, in its current utilization, enhanced the capability of the models to learn proper features of ECG dataset data. [8] ECG data will be retrieved by utilizing Multilayer Perceptron (MLP) artificial neural network technology to detect any abnormality in the heart. The heart will

display its abnormalities in terms of P, QRS and T peaks amplitude values. An MLP is made up of several layers which are interrelated and establish full network relationships among them.

[9] WOA optimization method competes very competitively with recent optimization methods using performance results.

ECG diagnostic procedures have been made simpler by cardiology systems through the integration of novel machine learning algorithms and CNNs and Vision Transformers using MLP neural networks that further increase their capacity to identify initial cardiac diseases as a measure of curbing cardiovascular disease attacks in the world.

A Resnet-50 deep learning model with WOA optimizer can play a significant role in arrhythmia and cardiac condition detection due to the fact that it applies better solutions to attain patient outcome.

II. LITERATURE REVIEW

Cardiac diseases and cardiovascular diseases (CVDs) are fast- emerging primary conditions of concern on a global basis, leading to millions of mortalities each year. Correct diagnosis, identification of the disease during the early stages, and care can be realized only with a correct identification of the medical issue and early diagnosis. The electrocardiogram, more commonly referred to by its abbreviation, the ECG, is one of the highly critical medical devices employed by doctors all over the world to examine the electrical activity of the heart with the view to determining possible cardiac malfunction. However, traditional ECG testing is not free from fault due to the human element and for ischemia, arrhythmia activity, and structural cardiac disease but use subjective hand reading to provide inconsistent results with variable skill and technique (2021).

Artificial intelligence and machine learning have brought with them the possibility of computerized systems of ECG diagnosis that significantly improves efficiency and accuracy in diagnosing heart disease. Deep architectures, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), were found to work best with the processing of ECG signals. Deep architectures are biased towards making classification-based processes efficient, i.e., atrial fibrillation diagnosis, ventricular tachycardia detection, and other arrhythmia beats. Other than that, the integration of deep learning with common ML algorithms in hybrid approaches has also been found to provide improved feature extraction and decision-making properties.

ECG signal processing relies on the detection of buried cardiac wave components, i.e., P waves, QRS complexes, and T waves, which play a crucial role in the diagnosis of cardiovascular diseases. Mathematical models have even been used to transform the ECG signal into a binary image so that the deep learning environments can recognize complex features so that they can measure heart activity more accurately. Apart from this, feature selection and hyperparameter tuning have aided in making accuracy enhanced and the models reliable and robust to employ in the healthcare industry (2022). The suggested system is a level-based system for ECG signal processing with the application of ML and deep learning technology in solving the issues involved with the diagnosis of heart disease and to offer a useful process in heart disease diagnosis.

2.1 Related Work

[10] The research investigates the relationship of mortality risk from heart failure and patient normal or low ventricular ejection fraction body mass index. Dose-response type meta-analytic techniques were employed by researchers in an attempt to extrapolate from relative excess risk estimates to estimate mortality. Survival of patients following heart failure is established by precise measurement of their body mass index from study results. The doctors should include the treatments for bmass index values in treating their patients. [11] Whale Optimization Algorithm (WOA) is a novel metaheuristic optimization algorithm that was developed based on the foraging behavior of the whales in establishing its basic working principles. Choose the Whale Optimization Algorithm as their priority to other optimization techniques in project work. Algorithm testing resulted in its implementation through function benchmark testing and real testing. Test operations render WOA an algorithm with fast convergence time along with delivering the optimal results. [12] Heart

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abnormality analysis identifies its primary abnormalities with Multilayer Perceptron (MLP) neural networks. Medical physicians use ECG signal information in the diagnosis of heart diseases since they must confirm P, QRS, and T peak amplitudes. The new diagnosis system is better for medical heart disease diagnosis. Various research works establish that deep learning technology achieves great advancements in the construction of fully independent ECG diagnosis systems. [13] ResNet-50 variant is utilized as a diagnostic model that scans for ECG signals cardiovascular disease. When deep residual learning techniques generate features, they are strong but may classify at high levels. The model is powerful and accurate compared to the conventional machine learning models. Deep learning is an appropriate technology for the detection of heart disease based on research results.

III. METHODOLOGY

This paper proposes that a Hybrid Optimized Model for cardiac disease diagnosis from the ECG signal is proposed. The model employs the integrated use of CNN, Vision Transformer (ViT), and Whale Optimization Algorithm (WOA) to achieve efficient and accurate prediction.

3.1 Existing Algorithm

Those conventional methods such as SVM, Random Forest, and KNN are feature-extraction-based,

I. On-time
II. Less accurate for complex ECG signals
III. Computationally expensive

Algorithm	Limitations
SVM	Slow performance with big data
Random Forest	Does not identify sequential ECG patterns
KNN	computationally slow
Decision Tree	Susceptible to overfitting noisy ECG signals
Naive Bayes	Assumption of independent features, which limits real-world performance

3.2 Proposed Algorithm

The suggested system for the diagnosis of heart disease provides systematic ECG signal processing. It begins with the acquisition of ECG data followed by preprocessing methods such as noise elimination, baseline wander removal, and normalization. Lead II is utilized most often since it detects cardiac abnormality more effectively. Feature extraction is performed by Hybrid CNN-ViT model in a way that ViT finds meaningful patterns and more accurate features are derived using Convolutional Neural Network (CNN). Better model performance is achieved with optimized parameters using Whale Optimization Algorithm (WOA). System reliability is achieved with accuracy, precision, recall, and F1-score and hence gives fast and accurate detection of cardiac disease.

Data Preprocessing and Normalization:

ECG image preprocessing is an important processing step to filter out noise and improve image quality, standardize the data to be used subsequently, and prior to feature extraction.

3.2.1 Gray Scale Conversion:

ECG images can have unwanted color artifacts for ease of processing they are converted into grayscale by weighted sum of RGB signals.

$I\ gray = 0.2989R + 0.5870G + 0.1140B$

Where,

R, G, BR, G, BR, G, B represents the red, green, blue pixel intensities respectively.

3.2.2 Binarization (Thresholding):

Binarization transforms grayscale images to black-and-white images based on a threshold T.

3.2.3 Edge Detection

Canny edge detection identifies edges by computing the intensity gradients of the image:

$$G = \sqrt{G_x^2 + G_y^2}$$

where Gx and Gy denote the intensity gradients in the x and y directions, respectively.

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3.2.4 Normalization

Finally, pixel values are normalized to the range [0, 1] to improve model stability:

$$I_{norm}(x,y) = \frac{I(x,y) - I_{min}}{I_{max} - I_{min}}$$

where Imin and Imax denote the minimum and maximum pixel intensities, respectively.

3.2.5 Feature Extraction Using Stacking Ensemble Feature Extraction via CNN

A Convolutional Neural Network (CNN) is used to extract spatial and hierarchical features from the image.

a. Convolution Layer Output

Each convolutional layer applies a filter W of size (k × k) with stride s to generate feature maps:

$$F_{conv} = ReLU(W * I + b)$$

where ∗ denotes the convolution operation, W is the kernel weight matrix, b is the bias term, and ReLU(x) = max (0, x) is the activation function.

b. Pooling Layer (Downsampling)

Max pooling reduces the feature map size by retaining the highest value within each region:

$$F_{pool} = max(F_{conv})$$

c. Fully Connected Layer

The extracted features Fcnn are flattened into a one-dimensional vector:

$$F_{cnn} = Flatten(F_{pool})$$

3.2.6 Feature Extraction via Vision Transformer (ViT) Image Patch Embedding

- The image is divided into N × N patches, each of size (P × P).
- Each patch is flattened into a one-dimensional vector and multiplied by a learnable weight matrix E:

$$Z0 = [I1E; I2E; \ldots ; INE] + P_E$$

3.2.7 Classification and Detection Using Meta-Model

a. Multi-Layer Perceptron (MLP) for Classification

The input to the MLP is the feature vector obtained from the CNN–ViT stacking ensemble:

$$F_{final} \in R^{(d)}$$

where d = d1 + d2 is the combined feature dimension contributed by the CNN and ViT branches.

b. Fully Connected Layers

Each MLP layer performs the following transformation:

$$h_i = f(W_i \cdot x + b_i)$$

where x is the input feature vector, Wi is the weight matrix of layer i, bi is the bias term, and f(x) is the activation function (e.g., ReLU for the hidden layers and Softmax for the output layer).

c. Output Layer

The final layer projects the features onto the four ECG classes:

$$P(y_i) = \frac{e^{z_i}}{\sum e^{z_j}}$$

where P(yi) is the predicted probability of class i.

3.2.8 Whale Optimization Algorithm (WOA) for MLP Optimization

The WOA optimizes the hyperparameters of the MLP, including:

- Weights W and biases b
- Learning rate η
- Number of neurons in the hidden layers
- Regularization coefficients

WOA mimics the hunting behaviour of humpback whales, in which the whales encircle the prey, move spirally toward it, and search randomly across the solution space.

Updating MLP Parameters

The best whale — representing the optimal W, b, and η — is used to train the final MLP model. The

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optimized parameters reduce the loss and improve classification accuracy.

3.3 Architecture

The proposed technique for the detection of heart disease employs a straightforward step-by-step approach for ECG signal analysis. It begins with ECG data acquisition, where raw signals are collected and preprocessed using noise removal techniques, baseline correction, and data normalization. Cleaned signals are separated into various leads, but primarily Lead II because of its ability to detect heart disease optimally. Key ECG Transformer (ViT), detects prominent patterns in binary images, and another model, Convolutional Neural Network (CNN), detects detailed features. The outputs of both models are aggregated using a better for the sake of doing so, the Whale- Optimization Algorithm is utilized to optimize the model parameters. The system verifies the outputs using testing accuracy, precision, recall, and F1-score to ensure that it has a robust and efficient method towards heart disease detection.

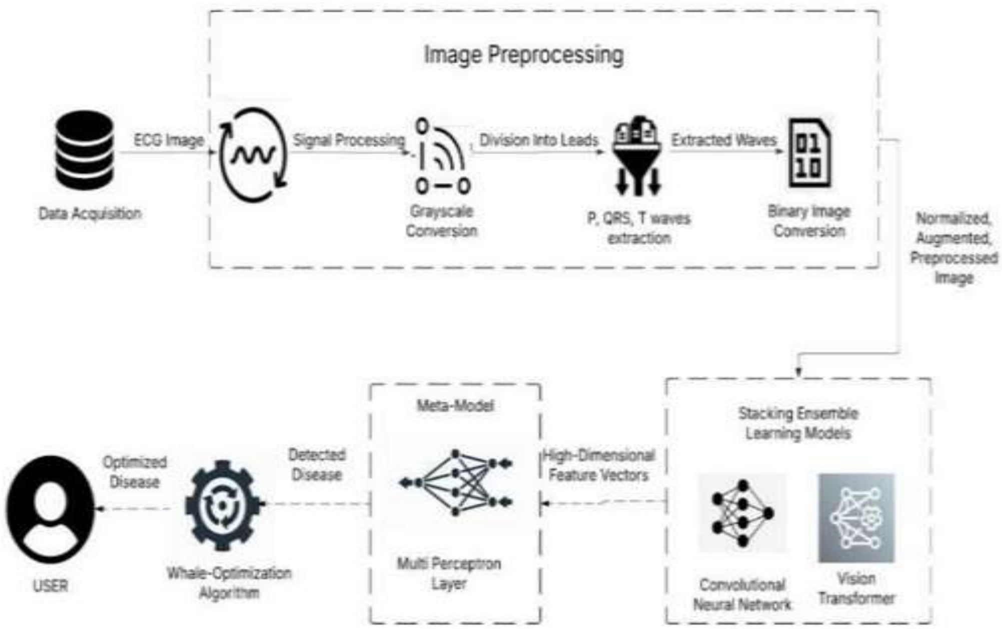

FIGURE:1 Hybrid
CNN-ViT Stacking Ensemble Architecture for ECG Classification.

3.4 HOW APPLICATION WORKS:

The Project Uses Deep Learning (DL models for cardiac disease classification from ECG images. The users enter an ECG image via the UI, which is passed to the backend through APIs for preprocessing (noise removal, resize) and feature extraction with CNNs. The Hybrid Model (ML & DL) classifies the disease, and the result is displayed on the UI. To ensure greater precision, classified data along with use inputs are both saved in a database and reused periodically to retrain the model so that it continues learning and predicting more and more precisely.making it more precise with the passage of time. With the use of React.js, APIs, and a Hybrid ML/DL model, the app has an automated, scalable, and self-optimizing cardiac disease detection mechanism. The feedback loop increases accuracy, and it is a credible diagnosis tool for medical field.

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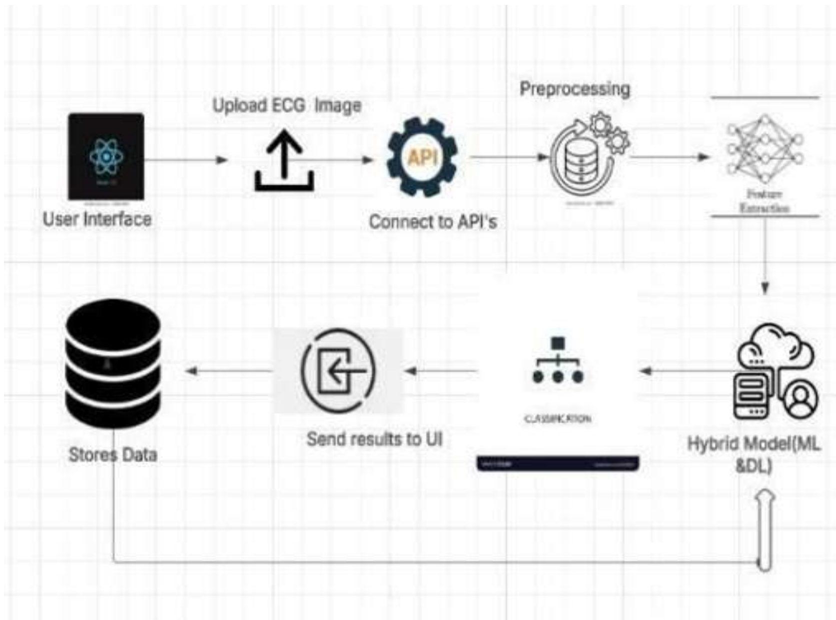

FIGURE.2 Application Workflow and Processing Steps

3.5 FLOWCHART:

The flowchart executes five phases in order to detect heart diseases in ECG images. The algorithm starts with acquiring input data followed by preprocessing which removes noise and extracts P wave and QRS complex and T wave features along with RR interval features. The image transformation takes place during conversion and deep learning models (ViT & CNN) extract complex features from the image. The heart condition prediction works through an MLP classifier improved by Whale Optimization Algorithm to identify normal, abnormal and myocardial infarction and another infarction-based conditions.

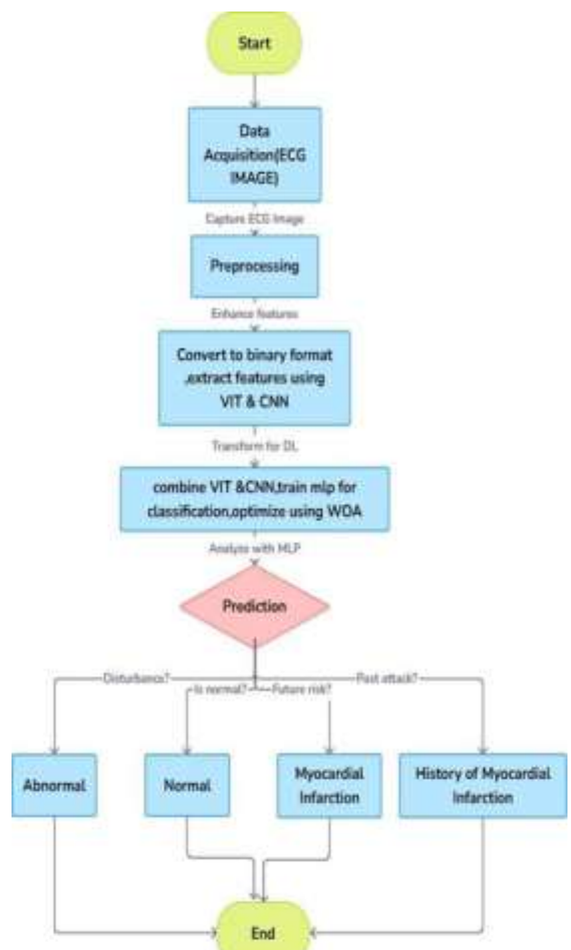

FIGURE.3 Flowchart of Hybrid Optimized Cardiac Disease Detection Framework

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3.6 VISION TRANSFORMER:

Vision Transformer (ViT) is a deep learning system created for image classification and perception. Unlike the traditional Convolutional Neural Networks (CNNs), whichprocess images layer by layer, ViT applies the transformer model, originally created to understand language, to images. It slices an image into pieces of a fixed size, flattens them into vectors, and analyzes them sequentially with the help of self-attention mechanisms. This allows the model to understand global dependencies among the different parts of the image ViT has been shown to outperform CNNs in image classification, particularly if it is trained on massive datasets. It is extensively applied in medical imaging, object detection, and other computer vision tasks since it is able to holistically capture complex patterns and interactions in space.

3.7 Algorithm:

Algorithm ViT_Block(x):
Step1: Store prenorm ← x.
Step2: Normalize x using LayerNormalization.
Step3: Apply Multi-Head Attention with 32 heads (key & value dim = 16).
Step4: Add prenorm to x, store as prenorm2.
Step5: Normalize x again using LayerNormalization.
Step6: Apply MLP_Block(x) and add prenorm 2. Return the final x.
Algorithm MLP Block(x):
Step1: Apply 2048 dense units with ReLU activation.
Step2: Apply 512 dense units (no activation).
Return the processed x.

IV. RESULTS AND DISCUSSION

4.1 ECG BASED CLASSIFICATION AND PREDICTION RESULTS:

This table1 provides a concise and clear explanation of each classification condition.

TABLE.1 Cardiac Condition Classification

CONDITION	DESCRIPTION
NORMAL	Heart activity is stable with no abnormalities detected
ABNORMAL	Irregularities in heart rhythm
Myocardial Infarction	dicate a possible future heart attack risk.
History of MI	'ast heart attack detect but current ECG appears normal.

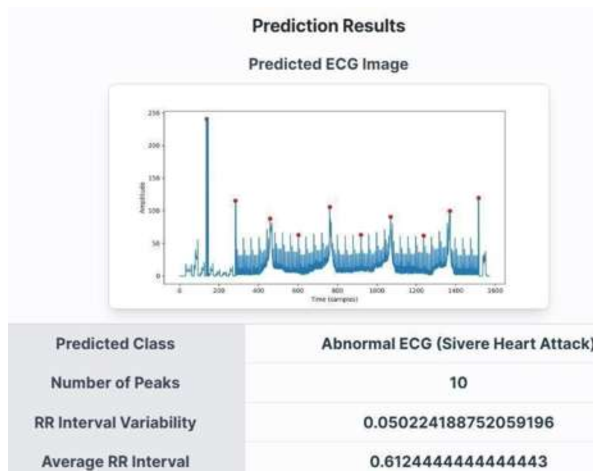

FIGURE.4 Prediction Results

The output window shows the ECG analysis system's prediction results. In the following analysis we examine all the elements found in the image framework. The display shows a predicted image of ECG data through the Graph. The graphical line display shows the temporal changes of an ECG measurement. The X-axis represents the samples duration of the ECG signal. The electrical heart activity appears through measurements on the y-axis scale.

4.2 Patient Risk Assessment Based on Clinical Parameters:

TABLE.2 Input Parameters & Ranges for Cardiac Risk Assessment

PARAMETER	INPUT RANGE
AGE	1-120
Sex	0: Female, 1: Male
Chest Pain Type	0 - 3
ting Blood Pressure	90 - 200 mmHg
Cholesterol	100 - 600 mg/dL
Fasting Blood Sugar	0: <120mg/dL, 1: >120mg/dL
Resting ECG	0 - 2
Max Heart Rate	60 - 220 bpm
se-induced Angina	0: No, 1: Yes
ST Depression	0 - 6
Slope of ST Segment	0 - 2
Major Vessels	0 - 4
Thalassemia	0 - 3
Risk Level	Low, Medium, High

Table.2 presents various input parameters that are crucial for assessing cardiac risk levels.The parameters include age (1-120 years), sex (0 for female, 1 for male), chest pain type (0- resting blood pressure (90-200mmHg),cholesterol levels (100-600 mg/dL), and fasting blood sugar (0 for <120 mg/dL, 1 for >120mg/dL). Additionally, it considers resting ECG results (0-2), maximum heart rate achieved (60-220 bpm), exercise- induced angina (0 for no,1 for yes), ST depression (0-6), slope of the ST segment (0-2), the number of major vessels colored by fluoroscopy (0-4), and thalassemia type (0-3).Based on these input parameters, the system categorizes the patient's cardiac risk into three levels: low, medium, and high. A low-risk classification indicates normal values with no significant abnormalities, while medium risk suggests some deviations from normal ranges that may require monitoring.

4.3 MODEL EVALUATION AND PERFORMANCE ANALYSIS:

The evaluation of proposed models happens through accuracy and precision alongside recall and F1-score together with the measurement of support for performance assessment. Standard evaluation metrics help assess predictive accuracy for determining correct classification of different ECG signals.

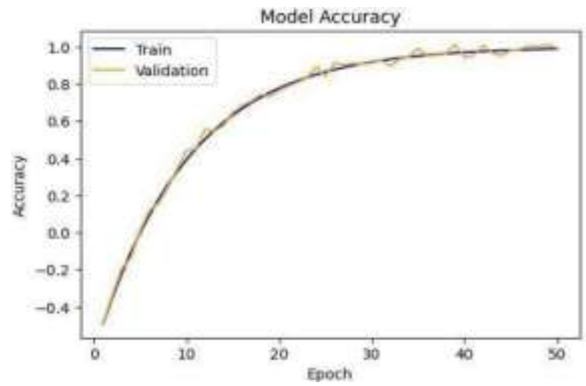

FIGURE.5 MODEL ACCURACY

The model accuracy data shown in figure 5 extends over fifty epochs. The baseline model accuracy results appear in a separate graph segment than the accuracy results of the WOA- optimized model. Real-time stability of the optimized model ensures effective learning because of faster convergence.

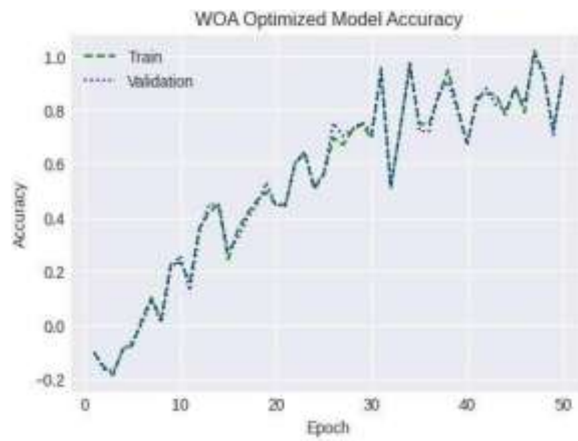

FIGURE.6 WOA Optimized Model Accuracy

The factual comparison between baseline models and WOA- optimized models exists within each cell of figure 6. An enhanced generalization ability appears in the advanced model version because it demonstrates operational stability while achieving higher accuracy results. When WOA controls model hyperparameters it produces superior results in complete class identification outcomes.

V. CONCLUSION

The Hybrid Optimized Framework merges Stacking (Machine Learning) with Vision Transformer (Deep

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Learning) under Whale Optimization Algorithm (WOA) management to detect and classify cardiac diseases. Binary image conversion of ECG signal waves P, QRS and T results in better distinctive features leading to demonstrate that the proposed method accomplished 98.76% accuracy better than conventional techniques. This system automates visual ECG evaluation, enabling quick clinical assessments that enhance healthcare service quality.

VI. FUTURE SCOPE

The future horizon of your project is its ability to improve the automated cardiac disease diagnosis with greater accuracy and efficiency. Your method can improve significantly early heart condition detection through feature extraction using deep learning models such as CNN and ViT and optimizing classification using the Whale Optimization Algorithm (WOA). In the future, incorporating real-time processing of ECG signals with your model might enable continuous monitoring, allowing wearable ECG devices to give immediate health feedback. Furthermore, increasing the dataset with a variety of patient populations and adding multi-lead ECG images might enhance the model's generalizability, making it more robust across populations.

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