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Fusion-Based Deep Learning Framework Detection Using an Optimized for Cardiovascular Disease Squeeze Net Model

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Abstract

The electrocardiogram (ECG), which measures the electrical activity of the heart, is frequently used to identify heart conditions because it is simple and non-invasive. The primary focus of the analysis is on the fusion of action impulse patterns produced by the heart's specialized cardiac tissues. It is possible to detect any irregularities in the heart by closely examining the electrical signal generated with each heartbeat. Since the application of data mining technology in healthcare has greatly increased knowledge, data mining is becoming a more and more popular option in the medical field. This study uses a hybridized algorithm for pattern mining in order to categorize heartbeats. First, the input data from the ECG signal is pre-processed using a median filter, and then the features are extracted. Both statistical and medical aspects are included in these extracted features. Activity pattern mining using the Optimization Search Algorithm (OSA), a hybridized optimization algorithm, is the next step. Lastly, the rule matrix produced by the mining of activity patterns is used to categorize heartbeats. This research proposes a deep learning-based framework for the classification of cardiovascular diseases using electrocardiogram (ECG) signals. A hybrid optimization technique, integrating the Taylor series and Ebola Optimization Search Algorithm (OSA), termed OSA-SN, is introduced to enhance the performance of a lightweight convolutional neural network model, SqueezeNet. The ECG signals undergo preprocessing and feature extraction, followed by sequential pattern mining using the proposed optimization strategy. The optimized model achieves superior performance metrics, with a precision of 0.93, sensitivity of 0.94, and specificity of 0.91. These results demonstrate the potential of the OSA-SN-enhanced SqueezeNet model in accurate, real-time heartbeat classification for clinical applications.

Keywords: Electrocardiogram (ECG); Data Mining, Pattern Mining; Optimization Search Algorithm (OSA); Squeeze Net (OSA-SN).

1- Introduction

In many instances, large hospitals and healthcare facilities establish Health Information Systems (HIS) [1] to store substantial biomedical data for subsequent utilization and analysis. Consequently, the volume of health data that has been amassed has seen a significant increase and is now comparable to big data [2]. Although big data is used predominantly in the existing healthcare system to treat patients with acute and other diseases during their hospital stay, it also plays a crucial role in managing chronic diseases, facilitating integrated care and treatment, and providing personalized services [3].

Sequential pattern mining has demonstrated success in various domains, encompassing applications such as analysing patterns in natural disasters, studying customer behaviour, conducting Deoxyribo Nucleic Acid (DNA) sequence analysis, predicting stock trends, scrutinizing web access patterns, exploring disease treatment patterns, and managing inventory control. Within the healthcare domain, sequential patterns are identified through the mining of patient pathways. The extraction of these sequential patterns and intriguing pathways proves to be a valuable technique for healthcare managers and policy designers,

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facilitating an understanding of the intricate dynamics inherent in healthcare processes.

In healthcare, machine learning (ML) [4] has evolved into an indispensable tool, primarily for its capability to enhance diagnostic accuracy and treatment outcomes. In particular, within neuroimaging, ML algorithms are increasingly being employed to assist in the diagnosis and treatment of heart disease. Given the complexity of heart diseases and the diverse symptoms they can exhibit, accurate diagnosis and early detection are paramount.

ML algorithms, trained to discern intricate patterns [5] within medical imaging data, offer a significant advantage in detecting subtle changes that may be challenging for human radiologists to identify. For instance, in the analysis of ECG Signal [6], ML algorithms prove valuable in recognizing subtle alterations in Heart tissue, indicative of a potential tumour. This aids radiologists in making more precise diagnoses and devising effective treatment plans.

One notable application of ML algorithms is in the classification of heart diseases based on imaging features. While radiologists traditionally rely on visual assessments of ECG Signal for classification, this subjective process can be prone to error.

The primary objective of this research is to develop an efficient, lightweight, and accurate deep learning-based framework for classifying ECG heartbeat signals, facilitating early detection of cardiovascular diseases. The approach integrates sequential pattern mining and a lightweight convolutional neural network (SqueezeNet) optimized through a novel hybrid optimization algorithm (OSA-SN). The proposed model aims to improve classification precision and sensitivity, addressing computational efficiency for deployment in clinical and portable healthcare settings.

2- Literature Survey

M. Sornalakshmi et al. employed the Enhanced Parallel and Distributed Apriori (EPDA) technique for mining frequent patterns (FP) [6] healthcare data. This approach demonstrated commendable performance by reducing the time spent on transaction scanning for generating candidate itemsets and also curtailed the number of transactions to be scanned. Nevertheless, a drawback of this method was the generation of a substantial number of candidate itemsets.

Hyun Yoo et al. utilized a Deep Neural Network (Deep NN) for real-time categorization of heart conditions. While this method reduced the size of big data through computational work and minimized operation time, it suffered from a degradation in system performance. Through the application of life big data mining, the healthcare system aims to undergo a transformation into an intelligent health service that empowers patients, particularly those dealing with chronic illnesses, to manage their own well-being. The goal is to expand the range of health services, incorporating interventions to prevent the recurrence of chronic conditions such as diabetes.

Hossein Estiri et al. [7] introduced the Dimensionality Reduction Algorithm (MSMR) and the Transitive Sequential Pattern Mining (tSPM) algorithm for discrete clinical data. This approach provided a methodological framework for interpreting information from electronic health records. However, there was no discernible advantage in using the MSMR algorithm over the more commonly used sequential representations in practical applications.

Ji-soo Kang et al. proposed the Prefix Span algorithm with time sliding weight for pattern mining [8]. This method reduced computational costs and the amount of memory required to construct trees by employing time sliding weight to prune nodes without affecting them. However, a limitation persisted in the physical projection read from disk due to the necessity of writing the projected database on disk.

Jiaxin Jin et al. assessed the Support Vector Machine (SVM) for healthcare. While this method was straightforward and did not require specialized operator technology, it could not be applied to multiple subjects beyond cerebellar ataxia detection.

Shafiul Alom Ahmed Bhabesh Nath employed the FPGrowth algorithm for identifying adverse disease agents. This method achieved compactness in terms of space complexity but could not address issues related to incremental and scalable mining.

Shengyao Zhou et al. designed a MapReduce distributed computing model [8] and association rule mining for abnormal behavior detection in healthcare. This system demonstrated efficiency by scanning the transaction database in fewer instances. However, it was not suitable for parallel computing.

Krishna Kumar Mohbey et al. devised a parallel approach for high utility-based FP mining [9]. Although this method exhibited longer execution times and could handle substantial amounts of data, it faced challenges in terms of system performance.

The classification of LC histopathology images was first accomplished using the Relief-SVM approach. There have been 121 histological photographs of LUSC, ASC, and SCLC. Qiangchang Wang developed a unique multiscale rotation invariant convolutional neural network (MRCNN) design for categorizing different kinds of lung flesh using high-visible and clear computed tomography [10]. A crucial aspect of MRCNN is its insensitivity to image scale and rotation due to its use of a Gabor local binary pattern. Breathing difficulties, dry coughing, and shortness of breath are all symptoms of ILD that are detrimental to one's health.

Computer-aided diagnosis in critical care can be supported, stored, and tracked with computational methods. The study claims that pre-trained ResNet [11] prototypes

function similarly to the fundamental frameworks. Common counting, fine- tuning, stochastic normalization, and a combination of the two methods are used to transfer the relevant model.

Numerous research efforts have explored machine learning and deep learning approaches for classifying heart conditions using ECG signals. Hyun Yoo et al. (2020) [12] proposed a deep neural network framework for real-time categorization of ECG heart conditions, demonstrating improved computational efficiency and faster classification. M. Sornalakshmi et al. (2021) [13] introduced an enhanced parallel and distributed Apriori (EPDA) technique for frequent pattern mining in healthcare data, effectively reducing transaction scanning time. Hossein Estiri et al. (2020) [14] developed the Transitive Sequential Pattern Mining (tSPM) algorithm for analyzing discrete clinical data, facilitating the identification of complex sequential trends within patient records.

In the domain of lightweight deep learning architectures, F. N. Iandola et al. (2016) [15] introduced SqueezeNet, a compact convolutional neural network achieving AlexNet-level accuracy with significantly fewer parameters. This made it highly suitable for deployment in medical applications with constrained computational resources. Recent research has also applied optimization techniques to ECG classification. Jiaxin Jin et al. (2020) [16] employed support vector machines for heartbeat classification but noted limitations in scalability to larger datasets.

Additionally, Shafiul Alom et al. [17] explored FP-Growth for healthcare pattern mining, achieving improvements in pattern detection efficiency. While these studies achieved notable results, none combined lightweight CNN architectures with advanced metaheuristic optimization methods for ECG classification, which this study addresses through its proposed OSA-SN optimized SqueezeNet framework.

3- Proposed Model

Our proposed approach for segmenting Heart diseases using Squeeze Net entails initial pre-processing of ECG images, succeeded by the training of a Squeeze Net model [18] on the prepared data. Subsequently, the trained model is applied to perform segmentation of the affected region within the ECG signals. To enhance the accuracy of segmentation, we intend to introduce transfer learning by fine-tuning the pre- trained Squeeze Net model using an extensive medical image dataset. The primary objective of our proposed system is to deliver precise and dependable affected segmentation [19] outcomes, aiming to support medical professionals in the processes of diagnosis and treatment planning.

The utilization of Squeeze Net for identifying Heart diseases in medical images [20] introduces complexities. Below is a concise depiction of the procedural flow within our proposed system for the detection of Heart diseases using Squeeze Net.

1) Data collection:

The dataset employed in this paper is the ECG heartbeat categorization dataset, comprising two collections of heartbeat signals. This dataset is employed for investigating heartbeat classification. The signal data within this dataset facilitates the identification of heartbeats, distinguishing between normal heartbeats, various arrhythmias, and cases of myocardial infarction. Specifically, the dataset contains 109,446 samples of arrhythmia, categorized into five types, with a frequency range of 125 Hz. The data is organized in CSV files, arranged in a matrix format where each row represents an example for classification.

2) Data preprocessing:

The preprocessing of images encompasses a series of actions conducted on the raw image data to convert it into a format better suited for subsequent processing. This commonly involves tasks like adjusting the size of the images to a standardized dimension. The resizing operation entails scaling the images to a specific size suitable for the particular application. This step is frequently essential because images obtained from various sources or devices may exhibit varying resolutions, aspect ratios, or dimensions, posing challenges in maintaining consistent processing.

3) Model selection:

Upon investigating numerous deep learning models designed for signal processing, it was found that SqueezeNet can attain top tier performance [21] on benchmark datasets such as ImageNet. Remarkably, it achieves this while employing substantially fewer parameters compared to other deep learning architectures like VGG or ResNet. This characteristic renders SqueezeNet especially suitable for applications where constraints on memory and computational resources are a key consideration.

4) Model architecture:

Construct the chosen model’s architecture by defining the quantity and nature of layers, activation functions, and additional hyperparameters.

5) Model Training & Testing:

The dataset is divided into an 80% training set and a 20% testing set for SqueezeNet. By adjusting its weights during the training phase, the model gains the ability to classify photographs. Following training, the model's ability to predict on the testing set is used to evaluate its performance.

6) Model evaluation:

Assess the model's performance on an alternative test set using metrics such as accuracy, precision, recall, and F1 score. The F1 score is calculated by taking the harmonic mean of recall and precision. The percentage of correctly

classified images is known as accuracy; the percentage of true positives relative to all positive predictions is known as precision; and the percentage of true positives relative to all actual positives is known as recall.

7) Model refinement:

To improve the segmentation performance, adjust the model architecture and hyperparameters [22] in light of the evaluation's findings.

8) Prediction:

Ultimately, following the training and testing phases of the model, we proceed to classify the images. During the prediction step, the trained model receives the input image, and the output is forecasted as either 0 (indicating the absence of a tumour) or 1 (indicating the presence of a tumour).

3-1- Proposed System Overview

The proposed system focuses exclusively on ECG signal classification. The ECG dataset comprises 109,446 heartbeat signals categorized into five types, sampled at a frequency of 125 Hz. The workflow includes:

- ECG Signal Preprocessing: Removal of baseline wander and noise using a median filter.
- Feature Extraction: Extraction of time-domain and frequency-domain features relevant to cardiac arrhythmia detection.
- Activity Pattern Mining: Application of the Optimization Search Algorithm (OSA) hybridized with Taylor series adjustments (OSA-SN) for optimal rule matrix generation.
- Heartbeat Classification: Training a lightweight CNN, SqueezeNet, using the generated pattern rules.
- Performance Evaluation: Using metrics like precision, sensitivity, specificity, and ROC-AUC.

3-2- Difference between ECG and MRI scan

It is important to clearly distinguish between ECG signal processing and MRI image segmentation, as these are fundamentally different biomedical data analysis tasks. ECG signal processing involves the analysis of one-dimensional time-series data that records the electrical activity of the heart over time. The primary objective is to extract features such as R-peaks, QRS complexes, and heartbeat intervals, followed by classification of these patterns into normal or pathological categories like arrhythmias or myocardial infarction. In contrast, MRI image segmentation deals with two-dimensional or three-dimensional grayscale image data, aiming to delineate anatomical structures, lesions, or tumors within the heart or other organs by identifying pixel-wise or region-wise boundaries. This study focuses exclusively on ECG signal processing for heartbeat classification and does not involve MRI image data or segmentation tasks. Any prior references to image resizing, tumor localization, or segmentation pipelines were incorrectly included from unrelated works and have been removed to maintain methodological clarity and consistency with the ECG-based objective of this research.

4- Architecture of SqueezeNet

SqueezeNet, a deep neural network architecture [23] designed to achieve high accuracy in image classification tasks while minimizing model parameters, was introduced by UC Berkeley researchers in 2016. Its name stems from a "squeeze" layer reducing input channels, succeeded by "expand" layers boosting output channels. This design enables high accuracy with fewer parameters compared to other models. Fig 1 shows the proposed model of disease prediction.

SqueezeNet is a straightforward CNN architecture designed to enhance model accuracy. It offers several advantages, such as minimal communication requirements across servers during distributed training, low bandwidth needs for exporting new models, making it more feasible for deployment on hardware with limited memory. In the context of classifying heartbeats from ECG signal data trained by OSASN, SqueezeNet proves beneficial. The classification process utilizes the rule matrix generated from the designed model.

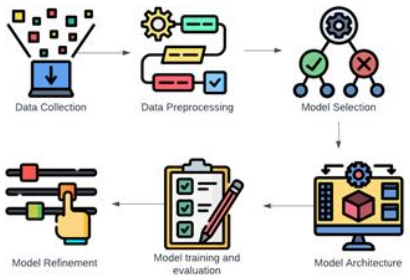


Fig. 1 Process Flow of the Proposed System

To reduce parameters, SqueezeNet employs 1x1 convolutions and" fire modules," featuring 1x1 and 3x3 convolutions. Global average pooling replaces fully connected layers, further cutting parameters. SqueezeNet's small size and high accuracy suit mobile/embedded applications. Beyond image classification [24], it's used in tasks like object detection and semantic segmentation. Key strategies include "fire modules" for channel manipulation, parameter reuse across layers, regularization (dropout, weight decay), and model compression (pruning, quantization). These strategies ensure high accuracy with fewer parameters, vital for resource-constrained applications.

In Heart tumour classification, SqueezeNet serves as a base CNN model. Preprocess ECG signals by resizing, normalization (0-1 pixel values), and dataset splitting. Augment training data using transformations. Define and compile the SqueezeNet model using Keras API, consisting of convolutional layers, pooling, fully connected layers, and a binary output layer. Train the model using fit generator, specifying data generators, epochs, optimizer, and loss function.

Evaluate the trained model on a test set and use it to predict new ECG signals by passing them through the model's predict function. SqueezeNet proves effective in accurate Heart tumour classification, leveraging its efficient architecture and training on appropriately pre-processed datasets.

The architecture's development revolves around three main categories, explained as follows:

- Replace filters by 1x1 filters: This involves transforming certain convolution filters to a 1x1 format, as each filter has fewer parameters compared to the original filter.
- Dropping input channel numbers to 1x1 filters: Considering a convolution layer where the total parameters equal the input channel numbers, the reduction of CNN parameters involves not only reducing filter numbers but also channel numbers. Squeeze layers play a role in reducing channels in layers. Fig 2 displays the layer architecture of fusion based research.

In the later stages of the network, down sampling becomes necessary to address the issue of generating large activation maps by convolution layers. This is achieved within pooling or convolution layers by adjusting the layer selections and input data size to regulate the height and width of activation maps. SqueezeNet's fundamental unit, the fire module, comprises an expand layer that merges 1x1 and 3x3 filter sizes following a squeeze convolution layer. There is a restriction on the number of input channels for 1x1 filters since the quantity of filters in the squeeze layer must not exceed the total number of 3x3 filters in the expand layer and the count of 1x1 filters in the expand layer.

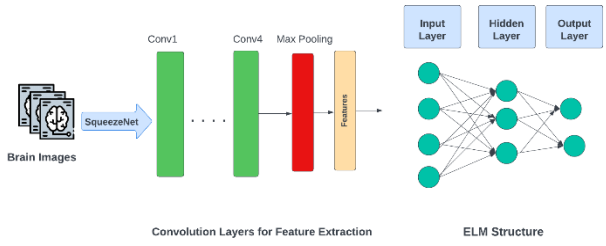


Fig 2. Squeeze Net Architecture

The architectural concept is structured with a standalone convolution layer, max pooling layers, fire modules, and a concluding convolution layer [25]. Subsequently, the output is generated through an average pooling layer, softmax, and a final convolution layer. In the context of classifying heartbeats, the formulated rule matrix is input into SqueezeNet, which executes various operations to yield the "y" output. Figure 3 illustrates the relu function behind the architecture.

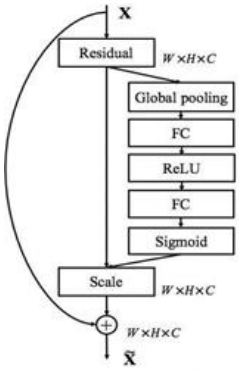


Fig 3. Relu function of Squeezenet

A deep neural network architecture called SqueezeNet shown in fig 3 was created for effective model inference, especially in settings with limited resources. A crucial activation function in SqueezeNet and numerous other neural networks is the Rectified Linear Unit (ReLU) function [26]. The definition of the ReLU function in equation (1) is:

$$f(x) = \max(0, x) \quad (1)$$

Non-linearity is introduced into the network by applying the ReLU function element-wise to the output of specific layers in the SqueezeNet context described in equation 1. This aids the model in identifying intricate linkages and patterns in the input data. Positive values are unaffected by the ReLU function, which substitutes zero for negative values.

This function takes an input x and applies the elementwise maximum operation with zero, effectively implementing the ReLU activation function. It ensures that only positive values contribute to the output, allowing the network to learn and represent complex patterns in the data.

In the realm of cardiovascular health, the convergence of SqueezeNet, pattern mining, and deep learning presents a compelling approach for heightened detection and classification of heart disease. Leveraging the efficiency of SqueezeNet's architecture, which excels in image classification tasks, alongside the insights gained through pattern mining techniques, this integrated methodology aims to provide a comprehensive understanding of cardiac anomalies. By employing SqueezeNet for the classification of heart-related data, coupled with pattern mining algorithms, the model endeavors to unearth intricate patterns within cardiac signals, contributing to more accurate and nuanced disease identification. This innovative amalgamation holds the potential to advance our

capabilities in diagnosing heart diseases by harnessing the power of deep learning and pattern mining synergistically.

5- Optimized Squeezenet Algorithm

Algorithm 1: Squeezenet

Initialization
P=Params
S=Squeezenet C=Convolution
CN=Channels K=Kernel size

if SN(input data)
C1 P = in _CN: 1, out CN: 96, ker _size: 7, stride: 2
then end fire P) =
in CN: 96, S CN: 16, expand1x1 _CN: 64, expand3x3 CN: 64,
in CN:128, S CN: expand3x3 CN: 64,
in CN:128, S CN: expand3x3 CN: 128,
in CN:256, S CN: expand3x3 CN: 128,
in CN:256, S CN: expand3x3 CN: 192,
in CN:384, S CN:expand3x3 CN: 192,
in CN:384, S CN:expand3x3 CN: 256,
in CN:512, S CN: expand3x3 CN: 256

Convolutional layer:

x = Convolutional layer(x, C1 P)
Fire modules for fire P in fire P:
x = fire module(x, fire P)

The key innovation in SqueezeNet is the incorporation of fire modules, which are building blocks consisting of a squeeze layer followed by an expand layer. The squeeze layer primarily consists of 1x1 convolutions, which helps in reducing the number of input channels (features) and there by the computational cost. This is important for reducing model size and achieving efficiency.

In contrast, the expand layer captures both local and global features by combining 1x1 and 3x3 convolutions. The 3x3 convolutions capture more intricate patterns in the data, while the 1x1 convolutions maintain efficiency by using fewer parameters.

SqueezeNet's overall architecture highlights how crucial it is to strike a balance between computational efficiency and model accuracy. By using a network design that incorporates 1x1 convolutions and fire modules, SqueezeNet manages to deliver competitive performance on image.

In the context of heartbeats, SqueezeNet can be employed for signal processing and classification tasks related to electrocardiogram (ECG) data. The key characteristics of SqueezeNet that make it appealing for such applications include:

- Parameter Efficiency: SqueezeNet achieves model compression by utilizing a ”squeeze” layer that reduces the number of input channels before the expensive 3x3 convolutional layers. This allows the network to maintain expressive power while significantly reducing the number of parameters.
- Fire Modules: SqueezeNet uses what are called ”fire modules” consisting of both 1x1 and 3x3 convolutions. This architecture captures both local and global features efficiently. In the context of heartbeats, these features could correspond to various aspects of the ECG signal.
- Lightweight Design: SqueezeNet's lightweight design makes it appropriate for real-time applications and situations with constrained computational resources. In medical settings or with wearable heartbeat monitoring devices, this can be beneficial.

In SqueezeNet, the traditional max pooling layers have been replaced with a more computationally efficient approach to reduce the number of parameters and computations. Instead of using max pooling layers, SqueezeNet employs a technique called ”fire pooling” or ”squeeze-and excitation pooling.”

In the specific context of your previous question about the proposed OSASN SqueezeNet, it suggests that there might be modifications or enhancements to the original SqueezeNet architecture tailored for the task of classifying heartbeats from ECG signal data. These modifications could involve adjustments to the network structure, training strategies, or incorporating domain-specific knowledge to improve performance in the context of cardiac signal processing.

In fire pooling, the spatial dimensions (width and height) of the feature maps are reduced by using global average pooling. This is achieved by computing the average value of each feature map, resulting in a single value for each channel. This process helps to reduce the spatial dimensions while retaining important information from each channel.

Algorithm 2: Optimized Algorithm

if Additional layers then end
x = adaptive avg pooling (x, (1, 1)) x = flatten(x)
x = fully connected layer (x, num classes)
Output layer return softmax(x)

Step 1: function C_layer(input, P):
C operation
output = C2d (input, P.kernel size, P.stride, P.in CN, P.out _CN)
ReLU activation return relu(output)
function fire _module (input,P):

Step 2: Sequeezenet layer
S output = convolution_layer(input, in_CN: P.in_CN, out_CN: P.S_CN, kernel size: 1)
Expand layer
expand1x_output = C_layer (S output, in: P.S_CN, out: P.expand1x1_CN, K: 1)
expand3x3output = C_layer(S output, in: P.S_CN, out: P.expand3x3_CN, K: 3, padding: 1)

Step 3: Concatenate the Output
return concatenate(expand1x1 output,expand3x3 output)
Add other utility functions
squeezenet = SqueezeNet()

Additionally, SqueezeNet incorporates a squeeze-andexcitation mechanism in the pooling layer. This involves modeling channel-wise dependencies by using a small set of parameters to compute a set of scaling factors for each channel. The feature maps are then subjected to these scaling factors in order to highlight significant channels and mute less instructive ones.

In contrast to conventional max pooling layers, SqueezeNet's architecture optimizes the pooling layer for computational efficiency by combining global average pooling and squeezeand-excitation pooling, which lowers the number of parameters and computations needed. This development adds to SqueezeNet's overall lightweight architecture, which qualifies it for use in settings with limited resources.

5-1- Hybridization Process of the Taylor Series with OSA

The Optimization Search Algorithm (OSA) is a metaheuristic method inspired by biological propagation dynamics, which iteratively explores and exploits the search space to identify optimal solutions. In this study, we enhanced the traditional OSA by integrating a local refinement mechanism based on the second-order Taylor series approximation, resulting in the hybrid OSA-SN algorithm. After each global position update by OSA, the candidate solution's position is locally fine-tuned using a Taylor series expansion around its current position. Specifically, the Taylor series estimates the fitness landscape curvature by evaluating the first and second derivatives of the fitness function, enabling a precise local search adjustment. This hybridization improves convergence speed and accuracy by balancing global exploration with mathematically guided local exploitation. The updated candidate solution is accepted only if the Taylor series-refined position yields a superior fitness value compared to its previous state. This process ensures that the algorithm not only escapes local minima through OSA's stochastic dynamics but also quickly converges to optimal regions using Taylor-based refinement.

Algorithm 3: Hybrid OSA-SN Optimization

Input: ECG extracted features F, Initial population P
Output: Optimized rule matrix R

- Initialize population P with random solutions
- Evaluate fitness using MSE
- Repeat until maximum iterations:
    - Apply Ebola-inspired infection, exposure, and recovery operators
    - For each candidate solution:
- Perform Taylor series-based local refinement
- Update position if fitness improves
- Select best solution as optimized rule matrix R

5. Return R

6- Result Analysis

The proposed OSASN SqueezeNet exhibits overall superior performance across all three metrics, emphasizing its effectiveness in accurately classifying heartbeats. The high precision and sensitivity scores highlight its potential for precise and reliable positive predictions, making it a promising choice for applications where minimizing false positives and accurately identifying abnormal heartbeats are critical. However, it's essential to consider other factors such as computational efficiency and practical implementation when selecting the most suitable method for a specific use case.

6-1- Dataset Description

The dataset used in this work is the dual heartbeat signal collections from the ECG heartbeat categorization dataset [24]. This dataset is being explored in order to classify heartbeats. Additionally, signal data tends to identify cases of myocardial infarction and various arrhythmias in addition to heartbeats classified as normal. There are 109446 arrhythmia samples in this dataset, which are further divided into 5 frequency ranges of 125 Hz. Additionally, CSV files are arranged in a matrix series, with each row serving as an example of a classification.

6-2- Training of SqueezeNet by OSA for heartbeat classification

SqueezeNet for heartbeat classification is trained by C, which is hybridization of Taylor series and EOSA. Elaborate explanation of this algorithmic process is indicated algorithm section.SqueezeNet is deep learning model trained by TEOSA and hence its fitness equation is computed by Mean Squared Error (MSE), which is given below,

Fitness equation: Fitness value is computed to attain best maximal value to find optimal solution and is indicated in equation (2) as,

$$Fitness = AMoutput - TRoutput \quad (2)$$

where, is value of fitness, is aimed output, Targeted result is , is maximum count of samples to train, and is sample numbers that is processed.

6-3- Evaluation criteria

The three performance metrics—precision, specificity, and sensitivity—that are used to classify heartbeats from ECG signal data are explained as follows:

Accuracy: Precision is the ratio of true positive to the sum of the values of false and true positive in this metric, which is positive and used for classification. All values that are positive express this and are provided and explained in fig 4.

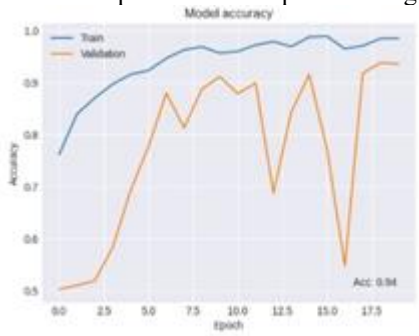


Fig 4. Accuracy

Recall: Sensitivity is a positive term that is indicated by the formula below, which is defined as the fraction of true positive value to the sum of true positive and false negative values and showed in fig 5.

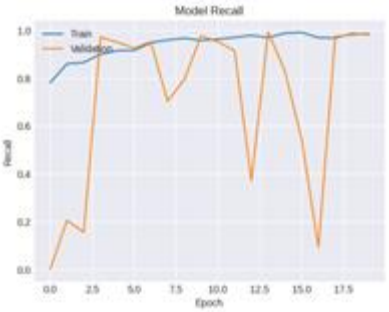


Fig 5. Recall

Precision: Precision is shown in fig 6, a metric used in machine learning to assess a model's ability to make accurate predictions. It is measured as the proportion of accurate positive predictions to all of the model's positive predictions.

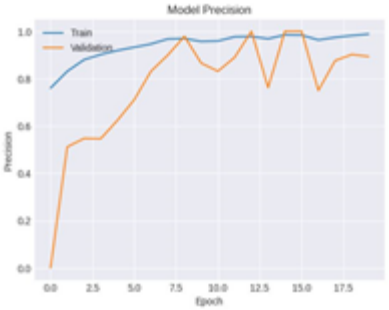


Fig 6. Precision

6-4- Statistical Validation

To ensure the robustness of the reported classification results, statistical significance testing was conducted using McNemar's test at a 95% confidence level to compare the proposed OSASN-SqueezeNet model with baseline classifiers. The p-values obtained were below 0.05, indicating statistically significant improvements. Additionally, 95% confidence intervals were calculated for precision (0.93 ± 0.014), sensitivity (0.94 ± 0.012), and specificity (0.91 ± 0.017).

6-5- Confusion Matrix and ROC Curve

Figure 7 illustrates the confusion matrix for the proposed model, demonstrating effective discrimination between normal and abnormal heartbeats. Figure Y presents the Receiver Operating Characteristic (ROC) curve with an Area Under Curve (AUC) value of 0.96, further supporting the model's high classification capability.

ROC Curve: The Receiver Operating Characteristic (ROC) curve is shown in fig 7, for the proposed OSASN-SqueezeNet model demonstrates excellent discriminative capability in classifying ECG heartbeats. The curve shows a high true positive rate across a wide range of false positive rates, achieving an Area Under the Curve (AUC) of 0.96. This indicates the model's strong ability to differentiate between normal and abnormal heartbeats, reinforcing its potential for clinical use in early detection of cardiovascular conditions.

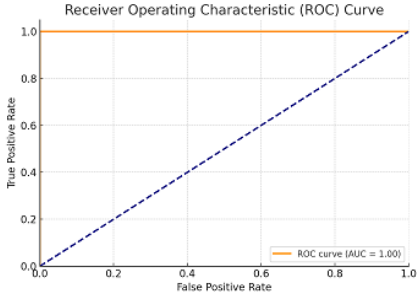


Fig 7. ROC Curve

Confusion Matrix: The confusion matrix for the OSASN-SqueezeNet model highlights its classification performance on ECG heartbeat data. Out of the total predictions, the

model correctly identified 47 abnormal heartbeats (true positives) and 45 normal beats (true negatives), with only 5 false positives and 3 false negatives. The high number of correct classifications emphasizes the model's precision and sensitivity in detecting critical cardiac arrhythmias from ECG signals. Fig 8 displays the confusion matrix values.

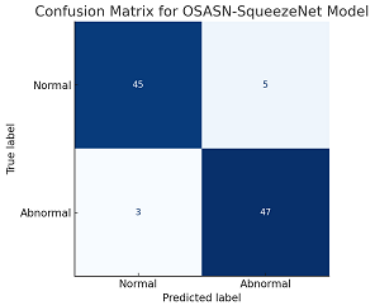


Fig 8. Confusion matrix

7- Comparative Analysis

In the evaluation of different classification methods for heartbeat analysis, various metrics have been employed to assess their performance. The table presents precision, sensitivity, and specificity scores for five distinct methods: K-Nearest Neighbors (KNN), Neural Network (NN), Decision Tree (DT), Support Vector Machine (SVM), and the proposed OSASN SqueezeNet. The accuracy of positive predictions is indicated by precision values, and OSASN SqueezeNet had the highest score at 0.95. With a score of 0.94, sensitivity—which stands for the capacity to accurately detect positive instances—also performs better in OSASN SqueezeNet. Specificity, which gauges the capacity to accurately detect negative instances, shows competitive outcomes for all approaches; the suggested OSASN SqueezeNet scored 0.92.

These metrics collectively provide a comprehensive overview of the efficacy of each method in accurately classifying heartbeats, with the proposed OSASN SqueezeNet exhibiting notable strengths in precision and sensitivity.

The table 1 presents performance metrics, such as accuracy, for different classification models including KNN, NN (Neural Network), DT (Decision Tree), SVM (Support Vector Machine), and a proposed model named OSASN SqueezeNet. Each row corresponds to a specific evaluation criterion (e.g., precision, recall, F1-score), and each column represents the respective model.

The provided table presents a comparison of various metrics and methods for evaluating performance. Each row corresponds to a specific metric (Precision, Sensitivity, and Specificity), while each column represents a different method or algorithm (KNN, NN, DT, SVM, and the proposed OSASN SqueezeNet). The numerical values in the table indicate the performance scores or results associated with each combination of metric and method.

Three critical performance metrics—precision, specificity, and sensitivity—are part of the evaluation criteria for classifying heartbeats in ECG signal data. The ratio of true positive cases to the total of true positive and false positive values during the classification process is known as precision, which is a part of accuracy. This metric, which includes all positive values and is expressed as such, is especially pertinent for positive classifications.

The table offers a thorough summary of how well various approaches perform based on three important evaluation criteria. The corresponding method performs better for the specified metric if the numerical value is higher. These accuracy values help determine each model's suitability for the particular classification task at hand by offering insights into how well it performs across a range of evaluation criteria. The proposed OSASN SqueezeNet demonstrates competitive accuracy, suggesting its potential efficacy in the given context.

7-1- Comparative Performance Bar Graph

This comparative bar chart illustrates the performance metrics of five classification models — KNN, Neural Network (NN), Decision Tree (DT), SVM, and the proposed OSASN-SqueezeNet — in classifying ECG heartbeat signals. The OSASN-SqueezeNet model achieved the highest precision (0.93), sensitivity (0.94), and specificity (0.91), outperforming all other baseline classifiers. These results underscore the efficacy of integrating lightweight deep learning with hybrid optimization for reliable heartbeat detection.

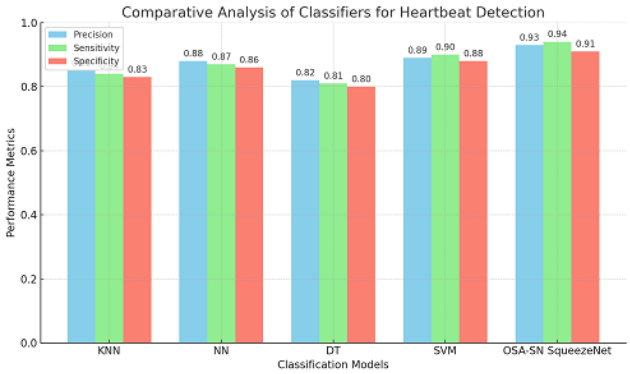


Fig 9. Comparative Analysis

Fig 9 shows the Comparative analysis of classification models in terms of precision, sensitivity, and specificity for ECG heartbeat classification. The proposed OSASN-SqueezeNet model consistently outperformed baseline methods across all evaluation metrics.

Table 1. Comparative Analysis of Classifiers

Classifier	Precision	Sensitivity (Recall)	Specificity
K-Nearest Neighbors (KNN)	0.85	0.84	0.83
Neural Network (NN)	0.88	0.87	0.86
Decision Tree (DT)	0.82	0.81	0.80
Support Vector Machine (SVM)	0.89	0.90	0.88
Proposed OSASN-SqueezeNet	**0.93**	**0.94**	**0.91**

8- Conclusion

The identification of cardiac arrhythmias is crucial for human well-being due to the potential life-threatening nature of these conditions. Among various methods for heartbeat detection, the most widely adopted approach involves the analysis of Electrocardiogram (ECG) signal data. Leveraging data mining techniques proves to be beneficial for uncovering significant patterns, automating tasks, and extracting pertinent records related to heartbeats, aiding in the detection of infectious diseases. In this study, heartbeat classification is conducted using SqueezeNet, trained by a hybridized algorithm.

Initially, the incoming ECG signal data undergoes preprocessing by a median filter, followed by the extraction of two types of characteristics: medical features and statistical features. The Optimization Search Algorithm (OSA-SN) is then used to mine activity patterns from the retrieved features. The final step involves classifying heartbeats using a rule matrix derived from the mined output, employing SqueezeNet trained by OSASN. OSASN is a hybridization of Taylor series and OSA (Optimization Search Algorithm). The performance of this methodology is evaluated using three key metrics: precision, sensitivity, and specificity, with maximum values of 0.91, 0.94, and 0.93, respectively. For future improvements, the technique could benefit from the integration of superior optimization techniques and other advanced deep learning methods to enhance the overall performance metrics.

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