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Leveraging Fuzzy C-Means and EfficientNetB0 for Improved ECG Image Classification

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Abstract

Electrocardiogram (ECG) diagnosis techniques provide more precise and more straightforward access to cardiovascular disease (CVD) detection than current clinical procedures allow. The presented framework combines EfficientNetB0 with Fuzzy C-Means (FCM) clustering to establish an innovative deep-learning hybrid model that optimizes ECG image classification. The system initiates its workflow with complete image processing that includes dimension adjustments along with normalization steps and color transformation before using EfficientNetB0 for deep feature acquisition. Using FCM clustering provides this method with a unique capability to generate fuzzy membership values that capture unpredictability and deviation found within ECG data. Two benchmark datasets undergo 5-fold cross-validation testing for evaluation of the model, with the first containing 1,376 ECG images spread across four diagnostic classes and the second having 3,264 images. Experimental tests show that EfficientNetB0-FCM produces better classification accuracy at 99.57% than other current CNN methods depending only on raw image features. Fuzzy membership elements are assessed regarding their ability to improve both precision and generalization using analyses that demonstrate the effectiveness of combined clustering.

Keywords: Fuzzy c-means, EfficientNetB0, ECG, Deep learning classification.

1 Introduction

Cardiovascular disease is a major non-communicable disease responsible for more than 17.6 million deaths in 2016 and is projected to rise to 23.6 million in 2030. Both diseases affect blood vessels by blocking them and forming clots; stroke and myocardial infarction are typical of them; moreover, cardiovascular diseases cause damage to multiple organs due to poor heart function. Electrocardiography is a common, inexpensive, and painless technique for evaluating general cardiovascular problems. It tracks the electrical signals of the heart and issues such as arrhythmias, myocardial infarction, and coronary heart disease. Electrocardiography is very useful in diagnosing heart diseases and can also predict upcoming coronary heart disease [1].

The ECG signal consists of five main waves: P, Q, R, S, and T. The letter P refers to the atrial repolarization; the letters QRS refer to the ventricular repolarization, including the letters Q, R, and S, respectively. The Q wave has a negative direction, the R wave has a positive direction, and so also the S wave has a negative direction. For this reason, in the ECG analysis, the QRS complex is significant because it stands for the ventricle of the heart in addition to masking the repolarization of the atrium since its amplitude is relatively high. The T wave corresponds to a period referred to as repolarization of the ventricle and the U wave, which could be an upslope after the T wave is positive in the same direction [2].

In the last several years, the expansion in usage of electronic health records, which can be related to large quantities of digital health information, and the advancement of data overseeing and interpretation facilities have revitalized machine learning in healthcare. Technological progress in the elimination of cloud computing, GPUs, and GPUs jointly with software methodologies has contributed to the enhancement and development of the current era of machine learning and deep learning. These may be used to recognize patterns within data for functions and are continually practiced in practice, such as speech recognition systems and image recognition systems. As a part of clinical electrophysiology, large digital electrocardiogram databases coupled with computational power have necessitated the use of machine learning to gather more data [3].

Cardiovascular diseases that affect the heart rhythm are the second most common type of disease in the world and can include minor disturbances and severe and ultimately fatal cases. Arrhythmias occur because the electricity inside your heart beats irregularly, and this can result in a heart rate that is too fast, too slow, or irregular. In the diagnosis of cardiac arrhythmias, electrocardiography is perhaps the most widely used tool, and other devices such as a Holter monitor with mobile functions can also be used. However, identifying the types of cardiac arrhythmias, especially in certain cases, such as asymptomatic atrial fibrillation, can be somewhat difficult due to some limitations resulting from the capabilities of data extraction from ECG strips and the opportunities for time series analysis. Artificial intelligence has also been closely associated with diagnosis and prognosis, except for the detection of atrial fibrillation through the use of machine learning. Previous work has detected atrial fibrillation with high sensitivity using triphenyl tetrazolium chloride; QRS complex analysis using support vector machine and multi-kernel learning; and other research in this regard uses R-wave derivatives to extract features for computer-aided medical decision-making [4].

Recently, this work evaluated how different ECG signal representations perform in classifying multi-label cardiovascular diseases (CVD). It explores the possibility of transforming multiple ECG signals into 2D images and compares the classification performance of image- and signal-based deep learning models. The results reveal that models using 1D ECG signals outperform those based on 2D transformations, suggesting that transforming ECG signals into 2D images does not provide any significant advantage for the PTB-XL database. Additionally, a multimodal fusion approach that combines 1D and 2D data did not outperform the 1D model alone, likely due to the lower performance of the imaging modality, raising concerns about the higher computational requirements of multimodal models [5].

To resolve these problems, a new study has started to analyze the application of clustering methods in deep learning models. Preprocessing techniques, like fuzzy C-means (FCM), can cluster the data according to their characteristics of similarity, which can be useful while classifying data as well. Among them, fuzzy C-means clustering is the most suitable for ECG data processing due to some of its features: data points belong to several clusters; the degree of membership in each of the clusters is possible. In this paper, to improve ECG image classification, we develop a hybrid deep learning model that incorporates the features of fuzzy C-means clustering and EfficientNetB0, which is a modern CNN model. To enhance the feature space and separate overlapping classes of ECG signals or when the features contain noises, fuzzy C-mean clusters will be used in this work. Indeed, the developed hybrid model is developed for solving several primary concerns in ECG classification. First, the EfficientNetB0 model is fine-tuned to provide both global and local features from 2D ECG images to avoid ambiguities in signal morphological differences. Second, similar characteristics of ECG features are clustered using fuzzy C-means clustering, which further enhances the possibility of noise by reducing the determination of exact boundaries and increasing the accuracy of the classification. Last, we test our approach on the public ECG dataset and show the effectiveness of the proposed approach regarding the common deep learning models' classification accuracy and speed. Thus, the list of contributions of this work is as follows:

- Propose a new approach combining CNN-based feature extraction along with fuzzy C-means clustering for ECG classification.
- Assess the effectiveness of this model through the 2D ECG image representation and conclude its capability of elevating the classification outcomes from the traditional one-dimensional-based approaches.
- Discuss the gain of the proposed approach over its best competitor and demonstrate the potential for its use in clinical decision support systems.

The rest of the paper, Section 2, describes the literature review of the ECG. After that, the material and methodology are described, and the types of methods used in our study are presented in Section 3. Then in Section 4, results and discussions of our work are presented. In addition, Section 5 contains the conclusion of the study.

2 Literature Review

In recent decades, great attention has been paid to the area of artificial intelligence and its applications, among which digital image processing, computer vision, and machine learning are of vision to fill the theoretical gap between humans and machines. This innovation has been adopted by many industries, among which include the medical field, especially when classifying, detecting, and identifying cardiac disorders, which are of great significance to health. Previous investigations of cardiac diseases have revealed that the combination of deep learning algorithms yields highly accurate results. Similar to the current research, deep learning is expanding in the context of medical imaging for detection and classification purposes [6]. For instance, 3D electrocardiogram signals have been largely studied as time series for detecting cardiac disorders. For instance, the echocardiogram and electrocardiogram are employed in diagnostic imaging to determine a disorder of the cardiac muscle. Echocardiograms commonly recorded by a stethoscope are useful in diagnosing cardiac abnormalities. However, many previous approaches have selected the feature set by hand, and this process is not fit for different application environments [7, 8, 9, 10]. Furthermore, time series ECG usually encounters problems, for example, baseline wandering and muscle contraction noise [7–10]. In specific, there are six limb leads placed at the extremities and six heart leads placed at other areas on the chest and limbs. These leads are important in making corrective assessments of the functioning of the heart. For instance, Noman et al. put forward a model of a 1D CNN that could learn raw cardiac signal features and another of a 2D CNN for time-frequency feature maps [11], and Xia et al. developed a mode for carrying out the automatic classification of ECG with wearable devices [12]. Other works have also preprocessed 1D ECG signals into 2D images for classification through other deep-learning models, including R-CNN [13, 14, 15].

The authors in [16] proposed a deep learning framework that was used for spontaneous arrhythmia diagnosis using a transfer convolutional neural network (AlexNet) model to classify the ECG signal into a specific cardiac condition. The arrhythmia identification rate was 98.51% and the test accuracy was, on average, 92%, which greatly confirmed the efficiency of the transfer learning approach to build an automated arrhythmia detection system without the need for extensive retraining. The authors in [17] used CNNs for feature learning, while LSTMs were used for temporal modeling using ECG data. When testing the accuracy on the PTB database, CNNs gave a result of 98.34%, while LSTMs tested a result of 99.69%, which considered the proposed system effective in processing user authentication. In [18], the authors presented a deep learning technique for VA detection, but the analyzed ECG signals were not first converted to image mode. These distorted images were then deconvoluted, normalized, and used to tune well-developed deep-learning models such as AlexNet, VGG-16, and Inception-v3. As a measure of the correctness of the proposed approach, MIT-BIH with cubic support vector machine was used with an accuracy of 97.6%. Table 1 shows the summary conclusion of the ECG detection methods on different datasets.

Table 1: Summary of literature reviews

Ref	**Method**	**Dataset**	**Accuracy**
Isin et al. [16]	Multiscaled fusion of deep CNN	Single lead short ECG	92%
Chamatidis et al. [17]	Faster R-CNN	PTB database	99.69%
Naz et al. [18]	Deep learning techniques AlexNet, Inception-v3, VGG-16, and transfer learning	MIT-BIH database	97.6%

3 Materials and methods

3.1 EffiecientNetB0

EfficientNetB0 is a state-of-the-art convolutional neural network (CNN) as shown in Figure 1 that was developed to efficiently balance network depth, width, and resolution through a technique called compound scaling [19, 20]. It is based on the premise that scaling these three dimensions uniformly results in a more efficient model compared to scaling them independently. The compound scaling formula used in EfficientNetB0 is:

$$d = \alpha^{\phi}, \quad w = \beta^{\phi}, \quad r = \gamma^{\phi} \tag{1}$$

where d represents the depth, w is the width, and r is the image resolution. α, β, γ are constants, and ϕ is the scaling factor. EfficientNetB0 serves as the baseline model in this family and is scaled up to create larger variants such as EfficientNetB1, B2, etc. The EfficientNetB0 model consists of building blocks based on mobile inverted bottleneck convolution layers (MBConv), along with squeeze-and-excitation (SE) modules. The MBConv layers help to reduce the computational cost by using depthwise separable convolutions, while the SE blocks adaptively recalibrate the feature maps by modeling inter-channel dependencies [21]. This improves the network's focus on important features, thus enhancing its representational capacity. EfficientNetB0 uses the Swish activation function given by:

$$\text{swish}(x) = x \cdot \text{sigmoid}(x) \tag{2}$$

where x is the input and $sigmoid(x) = \frac{1}{1+e^{-x}}$ is the standard sigmoid function.

This function introduces non-linearity while maintaining smoothness, which helps improve the overall performance.

3.2 Fuzzy C-Means

Fuzzy C-Means (FCM) is a powerful clustering algorithm that allows data points to belong to multiple clusters with varying degrees of membership. Unlike hard clustering methods, such as K-Means, where each data point is strictly assigned to a single cluster, FCM enables more flexibility by assigning membership values between 0 and 1 to each data point for all clusters. This soft clustering

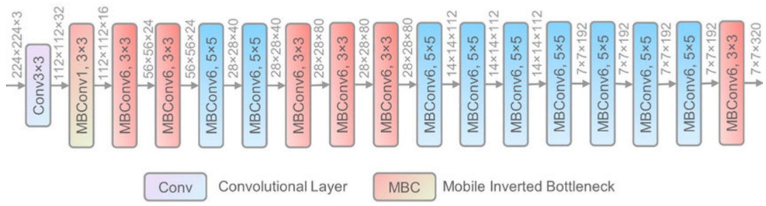

Figure 1: EfficientNet-B0 Architecture.

approach is particularly useful when dealing with datasets that have overlapping clusters or noise, as it can capture more nuanced relationships between data points and clusters[22, 23].

The objective of FCM is to minimize the within-cluster variance while considering the degree of membership for each data point. The membership values are calculated based on the distance between the data point and the cluster centroids, allowing FCM to iteratively update both the membership values and the cluster centroids until convergence as shown in algorithm 1 [24].

Algorithm 1 Fuzzy C-Means Clustering

Require: Dataset $X = \{x_1, x_2, \ldots, x_N\}$, number of clusters C, fuzziness parameter m, stopping criterion ε

Ensure: Final cluster centroids c_j and membership matrix U

Initialize random membership matrix U such that $\sum_{j=1}^{C} u_{ij} = 1$ for each i

repeat

  for each cluster $j = 1$ to C **do**

    Update centroid c_j:

$$c_j = \frac{\sum_{i=1}^{N}(u_{ij}^m x_i)}{\sum_{i=1}^{N} u_{ij}^m} \tag{3}$$

  end for

  for each data point $i = 1$ to N **do**

    for each cluster $j = 1$ to C **do**

      Update membership value u_{ij}:

$$u_{ij} = \frac{1}{\sum_{k=1}^{C}\left(\frac{|x_i - c_j|}{|x_i - c_k|}\right)^{\frac{2}{m-1}}} \tag{4}$$

    end for

  end for

  Calculate the objective function J_m

  Check for convergence: If the difference in J_m between successive iterations is less than ε, stop

until convergence

Algorithm 1 controls the level of membership fuzziness through its fuzziness parameter (m). Modeling the softness or crispness of cluster identification depends specifically on the fuzziness parameter (m). The algorithm operates as hard K-means clustering when m=1 because data points receive exclusive cluster assignments. The variable m drives the membership distribution across clusters when it surpasses 1, thus creating both cluster membership uncertainty and multiple cluster partial membership capability. The flexible setting of membership values enhances the clustering ability for complex or overlapping data distributions, especially when applied to ECG image analysis. For our proposed model, we selected m = 2 as the value for the membership degree because this value provides steady stability between soft membership and algorithm performance according to standard FCM implementations. The membership function applies the conventional FCM distance ratio approach according to the algorithm specifications: $u_{ij} = \frac{1}{\sum_{k=1}^{C}\left(\frac{|x_i - c_j|}{|x_i - c_k|}\right)^{\frac{2}{m-1}}}$

The designed mathematical model establishes that each data point achieves higher cluster membership proximity to its centroid and maintains a total membership of 1 across all points. The approach efficiently recognizes and captures medical image classification uncertainties, which leads to advanced decision-making within the model.

3.3 Proposed Hybrid Approach

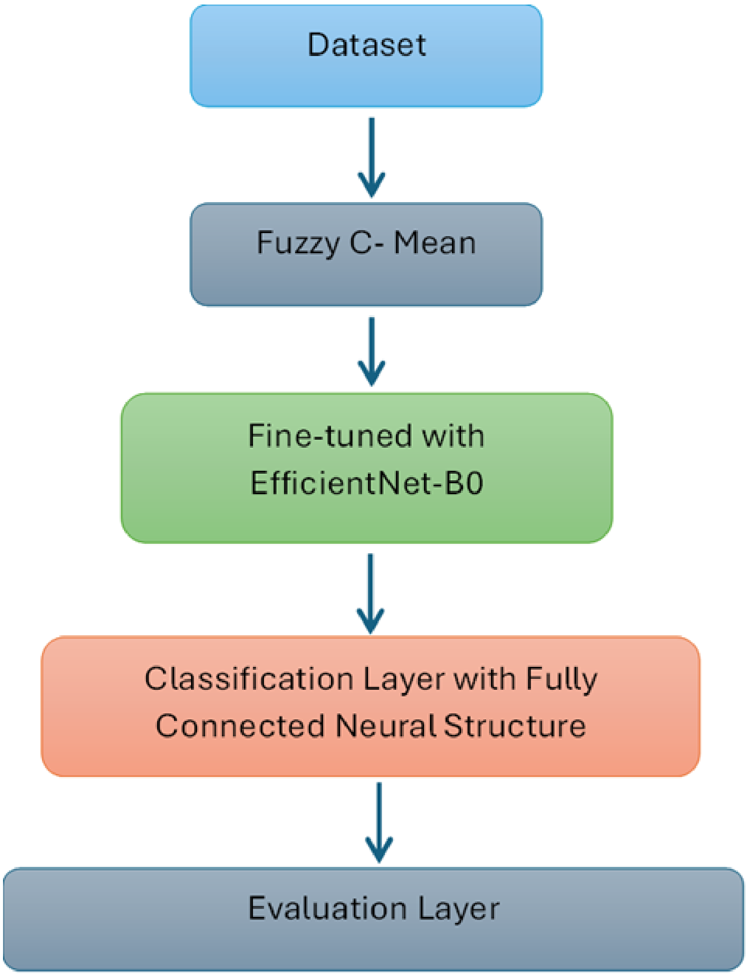

Figure 2: Proposed Hybrid Approach

The proposed hybrid approach combines EfficientNetB0 with the Fuzzy C-Means (FCM) clustering algorithm to improve ECG image classification according to Figure 2. The initial step applies FCM to identify essential ECG characteristics that form clusters that represent particular heart conditions. The FCM clustering method assigns each data point to multiple member categories through degree measurement so it can handle ambiguities within data. The model detects slight changes between different ECG waveform shapes because of its ability to result in enhanced and stable classification outcomes when paired with EfficientNetB0 deep learning features.

The FCM clustering produces its output features that flow into the EfficientNetB0 model, which is a deep neural network renowned for its feature extraction strength and efficient processing capability. The ECG signal patterns that EfficientNetB0 detects allow it to increase the discriminative strength of clustered features. First, the deep features progress through a fully connected neural network until reaching its final classification layer that gives probability distributions of target ECG categories. The combination of unsupervised FCM clustering techniques with supervised deep learning enhances the entire feature domain, which produces precise and comprehensible classification outputs. The framework leverages FCM's probabilistic methodology because it gives data points probabilistic rather than strict categorical assignments instead of rigid labels. Due to its probabilistic design, the model provides better handling for unclear or blended ECG readings. FCM's fuzzy membership vectors merged with EfficientNetB0's extensive feature extraction enables the model to maintain superior power and lower prediction imprecision.

The hybrid approach generates enhanced generalization together with improved noise resistance within ECG signals, which produces exact class boundaries that are dependable. The FCM-EfficientNetB0 configuration delivers enhanced classification results along with tools to interpret features obtained by the system. The supervised model uses FCM as an after-the-fact investigation tool to analyze how ECG features divide into multidimensional space.

This analysis follows the principles of present-day explainable artificial intelligence (XAI) since it uses unsupervised clustering methods to confirm the consistent nature of deep network-generated latent representations. Foreground Variability Clustering from FCM makes it possible to detect ambiguous feature zones that standard approaches can miss while generating probabilistic results during analyses. Along with our analysis, we showcase how model discrimination features connect to native data structures although class definitions are difficult to understand. Supervised learning, together with FCM interpretative analysis, provides the framework with a distinct strategy to examine model robustness while finding potential biases that guide data enhancement. The presented hybrid method adds value to current efforts that promote unsupervised methods as supplements to supervised deep learning networks for better model diagnostics and transparency. The FCM's feature of soft clustering adequately tackles uncertainty by providing probabilities for class assignments instead of fixed choices, thus enabling smooth processing of ambiguous ECG signal characteristics.

4 Results and Discussion

4.1 Dataset

The ECG image dataset of cardiac patients is collected under the supervision of Ch. The Pervaiz Elahi Institute of Cardiology, Multan, Pakistan, to facilitate scientific research on cardiovascular diseases [25]. The electrocardiogram images are divided into four distinct groups as demonstrated in Table 2, which contains 396 normal heart images and 351 MI images, 284 images showing prior MI, and 345 images displaying arrhythmia abnormalities. All images received a 224 x 224-pixel transformation, thereby creating 1,376 total images in the dataset. The classification system establishes exhaustive data sections about myocardial infarction, arrhythmia, and standard cardiac operation. The dataset represents a sample image as presented in Figure 3. The proposed model's generalization ability receives additional evaluation using a separate validation dataset to address validation loss oscillations. The extra dataset of ECG images from a distinct collection allows testing of the model's performance beyond its initial training set. Testing the model across different dataset types helps it avoid trivial pattern learning that forces the development of more generalizable information representation. The method lowers overfitting probabilities because it presents various realistic data patterns that match real-world conditions. A complete electrocardiogram image collection in the ECG Images Dataset of Cardiac Patients supports cardiovascular research through medical advancements [26]. It contains four primary categories: 800 images from patients diagnosed with myocardial infarction (MI), representing critical heart attack patterns; 1044 images from patients with abnormal heartbeat patterns indicative of arrhythmias or other cardiac irregularities; 172 images from individuals with a history of myocardial infarction, offering insights into long-term recovery and cardiac changes; and 1248 images from healthy individuals with no known cardiac issues, serving as a baseline for comparison.

Table 2: Image distributions based on classes.

Class	Image Distribution (Dataset 1)	Image distributions (Dataset 2)
Normal	396	1248
Myocardial infarction (MI)	351	800
Previous history of MI	284	172
Abnormal heartbeat	345	1044

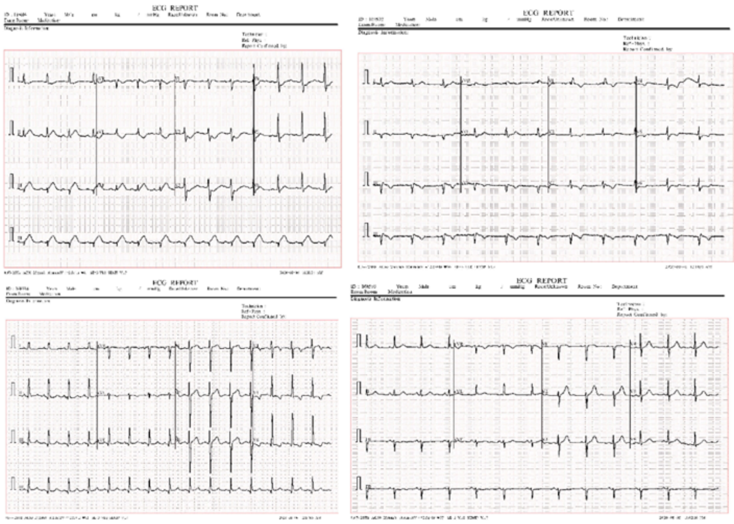

Figure 3: Samples of Dataset

4.2 Clustering results

Figure 4 shows how well the data points belong to the four clusters represented in it. The horizontal axis represents the index of the data points, and the vertical axis represents the membership degree, which shows how well each data point belongs to a particular cluster. Each line corresponds to a different cluster: self-selected clusters: normal (cluster 1), myocardial infarction (cluster 2), previous history of MI (cluster 3), and abnormal heartbeat (cluster 4).

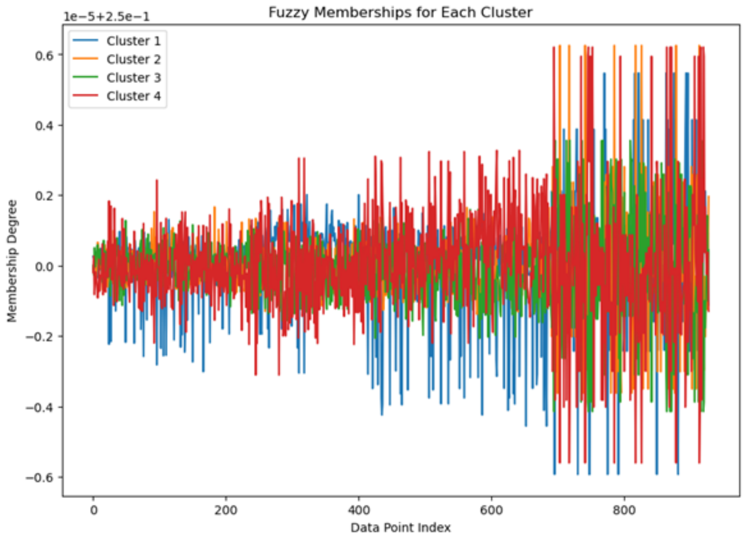

Figure 4: Fuzzy Membership for each cluster

Figure 5 illustrates the fuzzy C-means prototype on the data set and the PCA's two-dimensional clustering outcomes. The colored dots represent individual data points, with each color corresponding to one of four clusters: Image of a circle cluster The different circles are representative of four clusters: the blue circle for Cluster 1, the orange circle for Cluster 2, the green circle for Cluster 3, and the red circle for Cluster 4. The black circle symbols are large Xs that depict the locations of the centers of the clusters. This makes them have a few similarities where each of the clusters contains a similar data point, and the fourth cluster could be a new set of data points that are completely different from the three first clusters.

Figure 5 shows clusters with visual ambiguity as they appear overlapped and dispersed between each other, although the clustering method seems to work incorrectly. Visualization uses PCA to transform high-dimensional features into two components, but this transformation may alter how

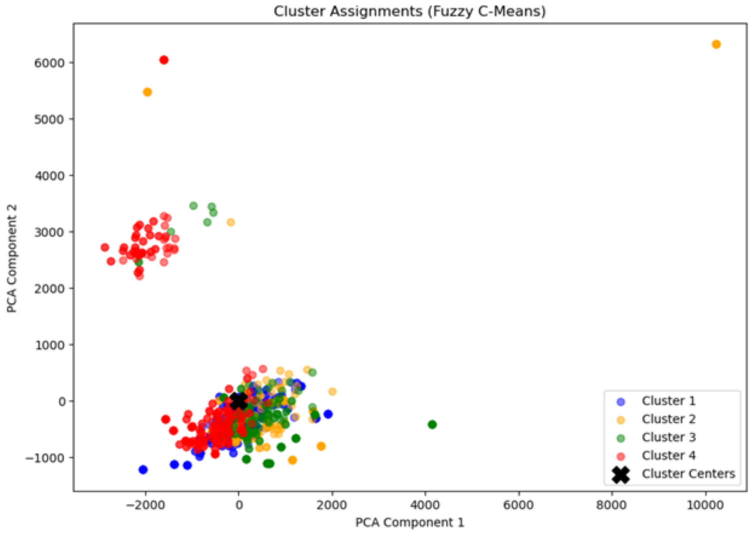

Figure 5: Cluster Assignments

clusters relate in space and how compactly they are grouped. The clusters achieve better separation in high-dimensional space because fuzzy membership values exist for computation. Hence the fuzzy c-means (FCM) assigns partial memberships through its algorithm when determining cluster membership because a data point can belong to different clusters at varying strength levels, which standard 2D PCA projections cannot effectively display. The clustering method plays an essential role in boosting feature representations by utilizing soft label assignments even though the visual representation is limited, which results in improved classification outcomes. The data presented in Figure 5 serves an exemplary purpose for demonstrating cluster behavior while avoiding usage as an accurate cluster validity assessment.

4.3 Performance Metrics

The performance of the proposed model was assessed using the following metrics: specificity, accuracy, precision, recall, and F1-measure, which are defined in Equations (5)-(9) [27].

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

$$Precision = \frac{TP}{TP + FP} \tag{6}$$

$$Recall = \frac{TP}{TP + FN} \tag{7}$$

$$F1 = \frac{2 * Precision * Recall}{Precision + Recall} \tag{8}$$

$$Specificity = \frac{TN}{FP + TN} \tag{9}$$

False positives (FPs), false negatives (FNs), true negatives (TNs), and true positives (TPs) are all measures of how well a model performs. Accuracy is the proportion of correct predictions. Precision is the proportion of correct positive predictions. Recall is the proportion of actual positives that are correctly predicted. The F-measure is a measure of how well a model predicts both positive and negative cases.

4.4 Experimental Results

The initial processing included multiple steps, beginning with image loading and finalizing with a resize to 224×224 pixels to achieve compatibility with the EfficientNetB0 model. The model training received an enhancement through normalization procedures. The ECG conditions within the dataset received four separate labels. We utilized k-fold cross-validation with k=5 to statistically evaluate the model across different subsets because it enhanced classification performance. The dataset was partitioned into five sections for grouping, with each section serving as the validation set while the remaining sections were used for training. This approach effectively mitigated overfitting and demonstrated that the model could successfully predict new data points. Furthermore, Fuzzy C-Means (FCM) clustering was rigorously evaluated against alternative clustering methodologies such as (K-means, and DBscan). The evaluation relied on average performance metrics from all folds, including accuracy, precision, recall, and F1-score, to provide the final assessment.

4.4.1 EfficientNetB0 without FCM

The EfficientNetB0 model was used as a baseline without any clustering techniques to evaluate its standalone performance in ECG image classification. The model extracted valuable features, which resulted in high accuracy rates across various ECG categories. The training curves indicated the successful knowledge acquisition from raw ECG images through stable convergence patterns. The complex nature of ECG signals caused the model to sometimes make incorrect classifications of samples, which showed substantial variations within their class group. The model performed feature analysis independently since it depended on deep representations to interpret borderline conditions. The results from EfficientNetB0 were favorable, but the model achieved fewer top performance points than cluster-based models did. The model performance was impaired when clustering-based preprocessing was omitted since it produced an inferior feature space that reduced both precision and recall metrics. The system operated efficiently because it removed the requirement for extra processing requirements. Missing better feature separation capabilities would produce superior outcomes in classification. The foundation established by EfficientNetB0 can support ECG classification activities yet requires clustering-based improvements to maximize its potential. Analysis of EfficientNetB0 reveals

Table 3: Classification Report for EfficientNetB0 without FCM.

Class	Precission	Recall	F1-score
Normal	0.98	1.00	0.99
Myocardial infarction (MI)	1.00	1.00	1.00
Previous history of MI	0.97	1.00	0.98
Abnormal heartbeat	1.00	0.96	0.98

excellent results for detecting all ECG categories shown in table 3. EfficientNetB0 reached a precision rate of 0.98 for normal cases, allowing it to generate a few wrong positive results with a perfect recall score of 1.00 that correctly identified all genuine cases. The assessment of myocardial infarction (MI) cases resulted in a perfect accuracy rate of 1.00 based on precision, recall, and F1-score measurements. The model successfully identified patients with a previous history of MI while achieving a precision of 0.97 and a perfect recall of 1.00, which generated an F1-score of 0.98. Nonetheless, the model showed a slight tendency to over-predict this class but proved its strong performance abilities. The precision value for abnormal heartbeat detection kept its value at 1.00 while recall decreased to 0.96 and produced an F1-score of 0.98, indicating several misidentified cases. The EfficientNetB0 model demonstrated outstanding classification performance with 0.9918 test accuracy, which establishes it as a very dependable tool for ECG-based medical diagnosis. Figure 6 illustrates the training and validation accuracy and loss curves for each of the five folds using the EfficientNetB0 model. The accuracy plot shows that all folds converge to high performance, indicating effective learning despite minor fluctuations during early epochs. On the loss plot, most folds display a rapid decrease, suggesting that the model quickly adapts to the ECG data, though occasional spikes appear, reflecting temporary instability or overfitting corrections. Overall, the consistency of these curves across folds demonstrates robust performance and strong generalization, as evidenced by the near-uniform high accuracy and low loss. These findings confirm that EfficientNetB0 effectively learns discriminative features from ECG images across multiple subsets of the dataset.

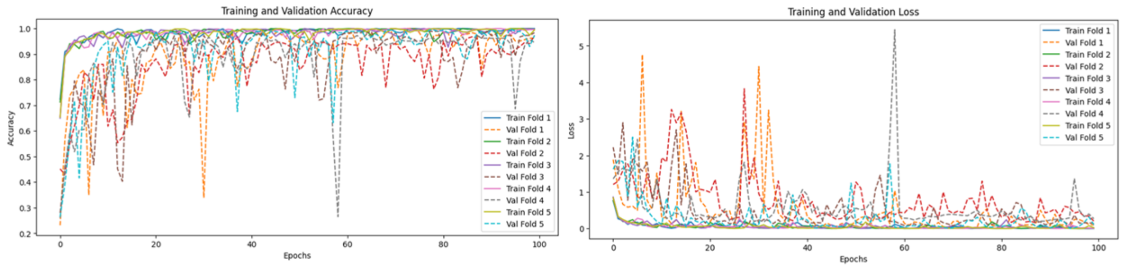

Figure 6: EffiecientNetB0 without FCM accuracy and loss for 5-fold

4.4.2 EfficientNetB0 with DBSCAN

The DBSCAN and EfficientNetB0 hybrid model optimized feature representation through its implementation of density-based clustering routines ahead of deep learning classification operations. The model used DBSCAN clustering to characterize data clusters by evaluating their density distribution, which led to noise reduction that potentially optimized classification precision. The approach struggled to handle high-dimensional ECG images because it resulted in unstable training performance. The model had reduced accuracy compared to the EfficientNetB0 standard because DBSCAN clustering was prone to uncertainties in parameter tuning when it processed ECG images with intricate distributions. A portion of ECG recordings was classified as noise, thus reducing training data availability, which degraded model generalization capabilities. The training loss curves that arose from this model contained additional variations, suggesting the features might be inconsistent in their learning process. The performance of DBSCAN as an anomaly detector was successful, although it occasionally produced clusters that did not create meaningful results, thus impacting classification accuracy. The designed model exhibited promising results, although its clustering performance could be enhanced through additional parameter optimization of DBSCAN. Table 4 demonstrates both severe class imbalances together with substandard results from DBSCAN integration using EfficientNetB0. The report shows that the model provides no advantage for the normal and previous history of MI classes since it achieves zero precision, recall, and F1-scores. The recall meets its maximum potential of 1.00, but the precision measures only 0.33 in the myocardial infarction (MI) category, which results in many false positive predictions. The model maintains complete precision for the abnormal heartbeat class since it always gets the classification right, yet its recall rate stands at just half, or 0.49, of detecting real abnormal cases. The current combination of DBSCAN does not effectively process ECG data variations across classes because it produces a highly imbalanced test accuracy value of 0.4142 that demands additional parameter optimization or alternative feature improvements. The accuracy and

Table 4: Classification Report for EfficientNetB0 with DBSCAN.

Class	Precission	Recall	F1-score
Normal	0.00	0.00	0.00
Myocardial infarction (MI)	0.33	1.00	0.50
Previous history of MI	0.00	0.00	0.00
Abnormal heartbeat	1.00	0.49	0.66

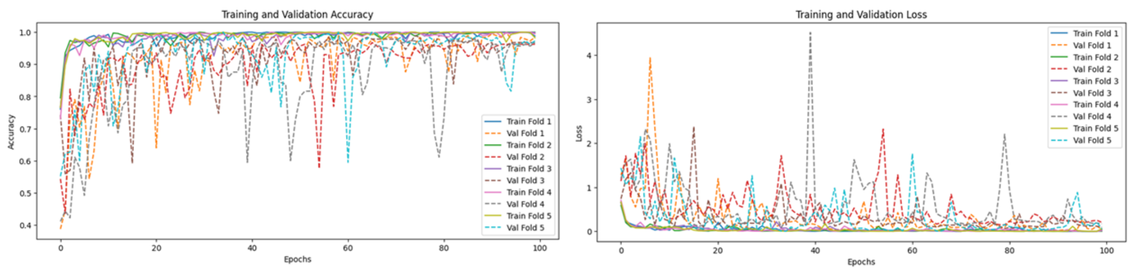

Figure 7: fiecientNetB0 with DBSCAN accuracy and loss for 5-fold

loss data for the hybrid EfficientNetB0 and DBSCAN model across five folds are depicted in Figure 7. The validation accuracy demonstrates significant variations during most folds even though the training accuracy increases rapidly, leading to potential inconsistencies when generalizing unseen data through clustering-based feature representation. During training, the loss demonstrates a downward pattern, yet the validation loss features intermittent spikes, although this behavior indicates possible feature overfitting or stability issues. The extent of convergence varies among different folds because DBSCAN operates variably across different ECG image partitions. The figure shows that specific splits allow the model to learn effectively, but its performance maintains inconsistent results across folds, thus requiring parameter optimization or different clustering techniques to achieve stable learning and enhance classification consistency.

4.4.3 EfficientNetB0 with K-Means

The purpose of combining K-Means clustering with EfficientNetB0 addressed the need to create organized processing for ECG image classification. K-means approached classification through the method of assigning samples to predefined clusters ahead of the process to refine feature representations. The new model achieved superior accuracy rates than DBSCAN, whereas it generated results that were not as effective as when employing EfficientNetB0 alone. The hard clustering feature of K-Means showed reduced flexibility because the algorithm failed to properly categorize ECG images when their features overlap. The model achieved faster convergence rates in its training curves than DBSCAN-based clustering, which demonstrated its efficiency capability. Cluster assignments proved inflexible because they resulted in improper classification of unclear instances. K-means provided lower computational expenses than fuzzy clustering algorithms, which supported its practical use in processing large databases. The preset number of clusters created limitations that needed proper adjustment to achieve maximum performance. The model worked with moderate success, yet additional clustering flexibility improvements would improve the classification results. The classification

Table 5: Classification Report for EfficientNetB0 with K-Means.

Class	**Precission**	**Recall**	**F1-score**
Normal	1.00	0.99	0.99
Myocardial infarction (MI)	0.99	1.00	0.99
Previous history of MI	0.99	1.00	0.99
Abnormal heartbeat	0.99	0.98	0.98

report of the hybrid architecture combining EfficientNetB0 with K-Means clustering for ECG image classification appears in Table 5. Evaluations showed remarkable outcomes where the normal group reached full precision and 0.99 recall together with an F1-score of 0.99, thus demonstrating almost flawless identification. The myocardial infarction (MI) class reaches exceptional performance due to its precision of 0.99, recall of 1.00, and F1-score of 0.99, which demonstrates how well the model detects MI cases. The model produces outstanding performance results for both MI patients who have experienced previous heart attacks by achieving 0.99 precision and 1.00 recall, which translates to a 0.99 F1-score. A precision value of 0.99 and a recall value of 0.98 lead to an F1-score of 0.98 regarding the abnormal heartbeat category even though its test accuracy reaches 0.9941. These metrics evidence the power of K-Means clustering to enhance EfficientNetB0 deep features, which lead to a balanced and reliable classification performance across all ECG categories.

The accuracy and loss values for EfficientNetB0 with K-means clustering under 5-fold cross-validation over 100 epochs can be viewed in Figure 8. Training accuracy makes a steady upward climb until reaching approximately 1.0, while validation accuracy shows an initial period of change before achieving stable enhancement, demonstrating robust generalization ability. Training loss declines steadily while stabilizing at a lower value, and occasional peaks appear in validation loss patterns, which may be due to sensitive subset selection or potential overfitting patterns. The model shows high effectiveness in ECG classification according to overall performance metrics, although certain improvements could be made to achieve better stability.

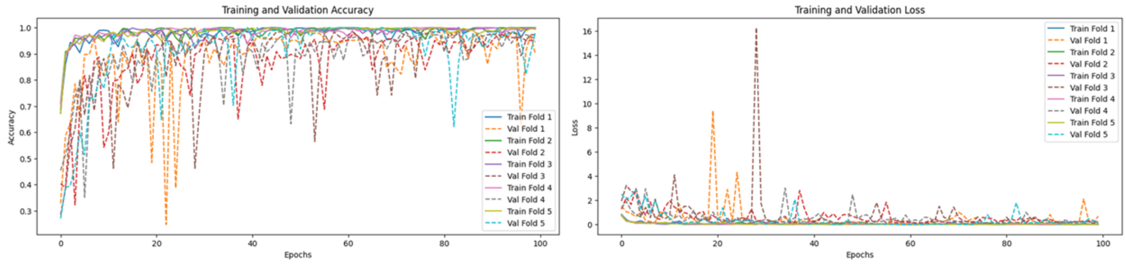

Figure 8: EffiecientNetB0 with K-Means accuracy and loss for 5-fold

4.4.4 EfficientNetB0 with FCM

The use of Fuzzy C-Means (FCM) coupled with EfficientNetB0 enabled superior accuracy through soft clustering solutions for feature characteristic representation. Such assignment of membership probabilities through FCM over K-Means enabled the model to detect fine differences within ECG image structures. The upgraded feature discrimination through this approach generated better results in classification effectiveness. The training maintained stable convergence along with reduced overfitting because of its refined clustering process. The implementation of FCM added computational challenges due to which training time exceeded existing models' speeds. Even though training time increased because of additional computational complexity, the model achieved better precision and recall which confirmed its strong classification abilities. The soft clustering method showed success in complex ECG pattern classification by lowering misclassification rates. Finding the right number of clusters presented a problem because it caused difficulties in parameter selection to achieve the best performance. The FCM-based approach delivered the best improvements to ECG classification, thus becoming the leading hybrid model among all tested methods. Table 6 demonstrates the classification

Table 6: Classification Report for EfficientNetB0 with FCM.

Class	Precission	Recall	F1-score
Normal	0.99	1.00	0.99
Myocardial infarction (MI)	1.00	1.00	1.00
Previous history of MI	0.98	1.00	0.99
Abnormal heartbeat	1.00	0.99	0.99

result of the EfficientNetB0 model combined with fuzzy clustering of C-means. The classification model excelled in all categories of the test data set through its evaluation of ECG images, where the normal class demonstrated 0.99 precision followed by a 1.00 recall score and an F1 score of 0.99, which indicates almost perfect identification of normal ECG readings. The model demonstrates perfect diagnostic competence in the detection of myocardial infarction by achieving precision, recall, and F1 score values of 1.00. The previous history of the MI class achieves an F1-score of 0.99 because it maintains perfect recall at 1.00 and a slight drop in precision down to 0.98, indicating the model produces minimal false-positive errors. The model distinguishes abnormal heartbeats effectively with a perfect precision of 1.00 combined with a recall of 0.98 and an F1 score of 0.99, which demonstrates its proficiency at recognizing abnormal patterns with a test accuracy of 0.9957. The performance of the ECG classification shows robustness when Fuzzy C-Means works with EfficientNetB0 since these metrics demonstrate enhanced feature representation capabilities. This leads to reliable classifications in each heartbeat category analyzed.

Figure 9 shows the training and validation accuracy, as well as the loss of the EfficientNetB0 model with Fuzzy C-Means (FCM) clustering, applied through 5-fold cross-validation over 100 epochs. The model consumes minimal iterations for training before attaining excellent results in training accuracy along with stable validation accuracy patterns, which imply strong generalization ability. Training loss reached a low, stable point, yet validation loss sometimes rose following data subset changes. The FCM-based model demonstrates better accuracy stability together with slightly reduced loss variations than K-means, thus proving potential success in ECG classification.

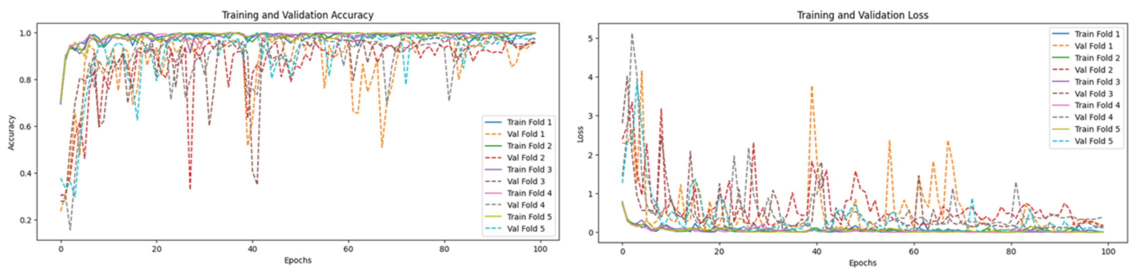

Figure 9: EffiecientNetB0 with FCM accuracy and loss for 5-fold

Table 7: Comparison between the proposed model and the recent techniques for the same dataset (ECG images for Cardiac patients)

Reference	**Year**	**Methodology**	**Accuracy(%)**
Khan, et al. [25]	2021	MobileNet v2	97.5
Abubaker and Babayiğit [28]	2022	CNN	98.23
Sadad et al.[29]	2023	Lightweight CNN	98.39
Proposed approach	-	Fuzzy c-means and EfficientNet-B0	99.57

The integration between fuzzy C-means clustering technology and EfficientNetB0 architecture executed superior classifying outcomes than alternative clustering methods. The classification report shows distinctively high precision, recall, and F1-scores on every ECG condition, which proves better model reliability. The FCM-based approach maintains stability because the training and validation accuracy and loss curves show minimal fluctuations that result in superior performance compared to the K-means algorithm. FMC demonstrates its effectiveness through these results by improving both accuracy and robustness in ECG classification.

4.5 Discussion

The combination of FCM customization with EfficientNet-B0 deep learning architecture provides key benefits to ECG image classification through their integration. The integration of Fuzzy C-Means (FCM) clustering with EfficientNet-B0 deep learning achieved an overall accuracy of 99.57%, according to Table 7, surpassing the results of similar research models. The proposed model successfully extracts relevant features and manages the uncertainty of the ECG data by applying soft clustering approaches, thus producing this result. The research studies presented in [25, 27, 28] performed their ECG-based cardiac classification evaluations on the same data sets and class-type groups. The proposed model demonstrated better performance than MobileNet v2-based methods and CNN-based approaches, resulting in a precision of 97.5% and a precision of 98.23% and 98.39%, respectively. Regarding robustness, our method delivers both strong recall at 99.5% and precision at 99.25%, thus showing its ability to effectively identify various cardiac abnormalities. The proposed hybrid technique proves effective based on consistent improvement metrics despite possible constraints due to the same dataset structures.

5 Conclusion

Fuzzy C-Means (FCM) clustering combined with the EfficientNetB0 pre-trained convolutional neural network represents an effective method for enhancing ECG image classification. This combined methodology benefits feature understanding by implementing fuzzy membership values to create better distinctions between myocardial infarction detection and previous history of MI and abnormal heartbeats. Results show that the model classification accuracy 99.57%, which demonstrates both deep learning and soft clustering techniques can benefit each other. The model shows weaknesses in specific folds because of overfitting yet remains susceptible to the initial cluster center placement during FCM runs. Future investigations should focus on improving FCM initialization protocols alongside testing the model's operational capability within medical facilities for reinforcing stability while increasing practicality across different healthcare domains.

Use of AI tools declaration

The authors declare they have not used artificial intelligence (AI) tools in the creation of this article.

Author Contributions

Conceptualization, Conceptualization, M.A.M., M.K.E., and K.A.; Methodology, S.A.E., M.A.M., A.A.A.; Software, M.A.M., and M.K.E.; Validation, K.A., S.A.E., and A.A.A.; Resources, M.A.M., and M.K.E; Data curation, S.A.E, and K.A.; Formal analysis, M.A.M., and A.A.A.; Investigation, M.A.M.; Project administration, M.A.M.; Supervision, M.K.E.; Visualization, K.A., and S.A.E.; Writing—original draft, M.A.M, and M.K.E.; Writing—review & editing, K.A. A.A.A. and S.A.E. All authors have read and agreed to the published version of the manuscript.

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Author contributions

The authors contributed equally to this work.

Conflict of interest

The authors have no conflicts of interest to report regarding the present study.

Data Availability Statement

Data is available online on: https://data.mendeley.com/datasets/gwbz3fsgp8/2

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