Empirical enhancement of EEG classification models for epileptic seizures using a fuzzy statistical perspective

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Abstract. The signals produced by an electrocardiogram (ECG) are made up of intricate pattern sequences that have a periodic structure. These pattern sequences contain an initial P-wave, which denotes the beginning of an ECG wave, a QRS sequence, which denotes the intensity of the pulse, and a T segment, which denotes the conclusion of the wave. Characteristics such as PR interval, QRS interval, QT interval, ST interval, R to R interval, etc. are employed to recognize chronic, ischemic, and other cardiac illnesses. These wave patterns need the simultaneous execution of many high-complexity signal processing operations to be classified into cardiac disorders. Signal pre-processing, feature extraction, feature selection, classification into epileptic and non-epileptic seizures, and post-processing are some of these operations. For each of these operations, researchers create a wide range of algorithms. These algorithms' performance differs significantly in terms of the quantity of leads utilized for ECG collection, filtering effectiveness, feature extraction & selection effectiveness, and classifier effectiveness. Thus, researchers and system designers have become unclear when choosing the optimum algorithm set for an application. This text offers a thorough analysis & design of fuzzy CNN model of a broad range of epileptic & non-epileptic seizure classification techniques to lessen ambiguity. Convolutional neural network (CNN) based models outperform other models in terms of general-purpose performance, whereas application-specific deployments need the employment of customized fuzzy CNN models. A significant area of research & development is presented by the observation that fuzzy logic techniques are not observed while constructing ECG classification models. Based on these findings, a new fuzzy logic-based classification method is provided in this text that employs quantization techniques to transform input ECG signals into fuzzy values. With these parameters and a specially created CNN model, it was possible to achieve an accuracy of 99.5% for diverse ECG datasets. This accuracy was compared to a number of cutting-edge models, and it was observed that the suggested model is quite good at categorizing ECG signals. The suggested technique was observed to be quicker than traditional procedures due to the usage of a fuzzy logic model, enhancing its scalability for a broad range of clinical applications.

Keywords: ECG, pattern classification, CNN, epileptic & non-eEpileptic seizure, healthcare, public health.

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1. Introduction

A challenging signal processing issue is classifying ECG data into cardiac disorders [1,2]. Effective signal capturing, pre-processing, filtering, segmentation, feature extraction, feature selection, classification, and post-processing blocks are all included in this. Each of these blocks has unique internal processing properties for certain signals. Therefore, an effective design of these internal blocks is required to create an effective ECG classification system [3]. Figure 1 shows a Generalized Block diagram for ECG classification, showing the data flow between various blocks. As can be seen from this block diagram, a huge classification of intricate operations are observed on an ECG wave before it is finally classified. The ECG signal is first recorded from a regular dataset or from real-time signal collection technology. Accuracy of data representation depends on how well this data was captured. After the data has been collected, a pre-processing block receives it. The design traits for any pre-processing block are as follows.

Signal normalization must be performed to make the signal compatible for feature extraction. The normalized signals are then given to a transformation unit, where various filters are applied to convert the signal into a wavelet domain, frequency domain, cosine domain, etc. Output signal should have minimal noise, maintain the pattern of the original ECG, and contain all of its properties. This block helps with feature augmentation, enabling the feature set to represent the ECG signal more fully. A feature extraction and selection unit receive each of these modified signals. The following features are retrieved and saved for system training: P-wave length, PR-segment, PR-interval, QRS duration, R amplitude, ST segment, PP duration, RR interval, etc.

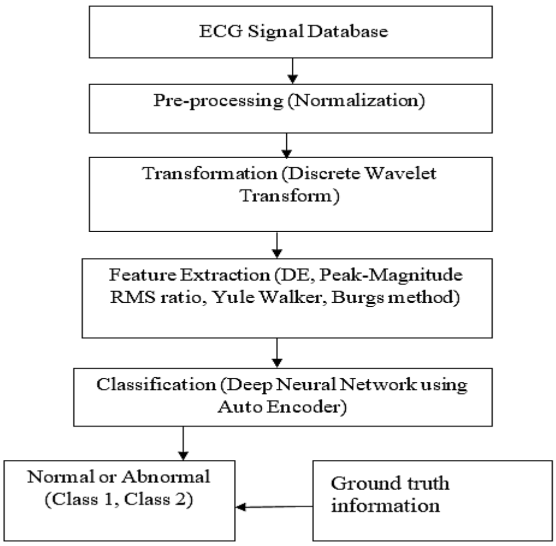

Figure 1. ECG classification process.

These selected signals are sent to classifiers such as neural networks, autoencoders, etc. These techniques employ hybrid and stand-alone architectures to improve classification performance [4]. Unfortunately, many combinations are available for the same classification of heart disease, making it difficult to choose the optimum implementation from among these structures. This text contrasts several machine learning models & architectures in terms of various performance measures and applicability to lessen this uncertainty [5]. The creation of a fuzzy statistical model for this application is then done, which will let researchers use it for high-performance ECG applications. Finally, this text closes with some thought-provoking conclusions regarding these algorithms and suggestions for how to make them better.

2. Literature review

A wide variety of models are proposed for ECG classification using deep learning. For instance, the work in proposes use of a support vector machine (SVM), Neighborhood Component Analysis (NCA)

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based convolutional neural network (CNN), and short-time Fourier transform (STFT) based classification models. These models achieved high accuracy on clinical ECG datasets, and thereby can be applied for real time heart disease prediction [6]. Similar to this work, the work in [7] proposes use of visual pattern features, finite impulse response (FIR) filter features, and probabilistic neural network (PNN) to estimate high level features and perform their classification. These models can classify ECG signals with over 94% accuracy on static and clinical datasets, making them highly usable for real-time deployments. Secondary features like dual heartbeat coupling [8], segment feature analysis [8], and eigen ECG network with time frequency analysis [9], are also proposed by researchers. These models aim to reduce the number of features needed for classification, thereby improving overall system speed while maintaining high classification accuracy.

Zhang et al., [10] proposes the use of multiple lead branch fusion networks, multiple ECG classification networks, and iVector based classification models for high accuracy ECG classification. These models can achieve an accuracy of more than 99% on different datasets and can be used for any clinical application. Doctors and clinical personnel use these models for high-efficiency ECG classification. Still, the computational complexity of these models is very high, thereby limiting their use to clinics where high-performance computing machines are available [11,12]. In order to reduce this complexity, Generative Adversarial Networks (GANs) [13], Multiple perspective CNNs [14] and recursive CNN [15] models are proposed. These models aim to reduce the computational complexity via high-efficiency feature extraction and selection, thereby achieving low delay, and high accuracy of ECG classification. Based on these models, it is observed that CNN-based models outperform other models like SVM, and artificial neural networks (ANNs) [16,17].

Thus, the proposed model utilizes a modified fuzzy CNN model for high accuracy and low delay ECG classification. The model is described in the next section and comparative analysis with other state-of-the-art models.

3. Proposed fuzzy CNN model for ECG classification

Based on the literature review, it can be observed that fuzzy logic approaches are not fully explored for the classification of ECG signals [18,19]. This is a significant improvement area because use of fuzzy logic can assist in reducing overall delay needed for classification while maintaining high classification accuracy performance. Furthermore, researchers have not yet explored combining fuzzy approaches with deep learning models. Based on these background observations, the proposed fuzzy CNN model for ECG classification initially quantizes ECG signals into 0 to 1, and converts quantized data into fuzzy ranges. These ranges are decided using a Mamdani fuzzy engine, observed in figure 2, wherein normalization and fuzzification processes are defined. In order to quantize the ECG signal, equation 1 is used as follows,

$$ECG_{out} = \frac{ECG_{in} - MIN(ECG_{in})}{MAX(ECG_{in})} \quad (1)$$

Where, ECG_in, and ECG_out are input and output values of ECG signal. These values are given to the fuzzification engine, wherein the following steps are executed,

- Number of fuzzy ranges are defined (k)
- A membership function (f) is defined for fuzzification, which can be either Gaussian, bell curve, Gaussian bell curve, etc.
- Quantized ECG data is converted into fuzzy values using equation 2 as follows,

$$ECG_{fuzzy_i} = \frac{f(ECG_{out}) * i}{k} \quad (2)$$

Where, i∈(1,k),and ECG_(fuzzy_i) is the fuzzy output value of ECG signal for the i^th range. These fuzzy values are given to a VGG-19 CNN model for training and classification. The design of the proposed VGG-19 CNN model is shown in figure 3, wherein all the layers and their interconnections are seen.

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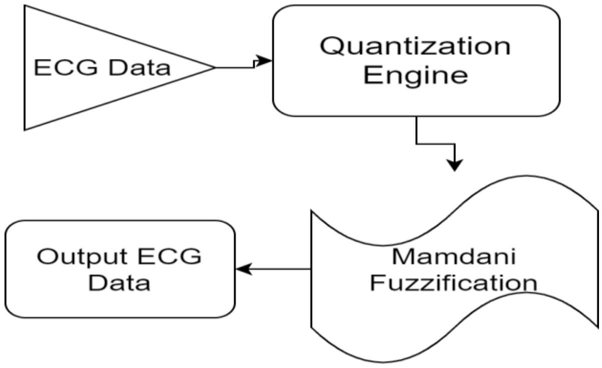

Figure 2. Quantization and fuzzification of ECG data.

The model uses following layers to extract deep learning features and utilize them for final ECG classification,

- The fuzzy ECG values are given to a 16x1 convolution layer, wherein a stride size of 5 is used. This layer uses a large number of overlapping windows to extract statistical features like minimum window value, maximum window value, average window value, variance of fuzzy ECG signals, standard deviation of signals, etc.
- All these values are activated using a rectilinear unit, which is governed using equation 3 as follows,

$$RELU_{out} = F\left(ECG_{fuzzy}\right) \quad (3)$$

$$when\ F\left(ECG_{fuzzy}\right) > 0, else\ 0$$

Where, $RELU_{out}$ is the output of RELU, while $F(ECG_{fuzzy})$ represents the statistical feature function F, when applied to the fuzzy ECG signal.

- Due to use of overlapping windows, the number of extracted features is very large in number. Therefore, a maximum pooling layer is used to select the features that have highest variance.
- In this case, top 50% features are passed to next layer, which reduces the feature vector's size and improves classification accuracy.
- The selected features are given to another feature selection layer named ‘drop out layer’.
- This layer selects only 10% of the features, and drops remaining 90% as per the feature variance.

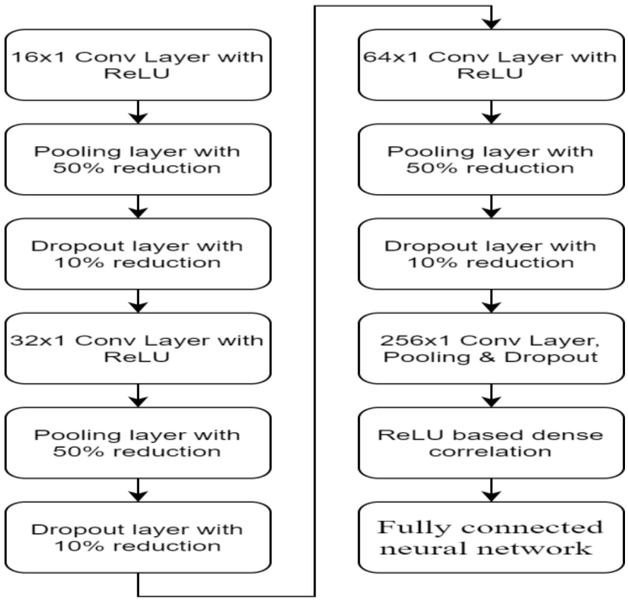

Figure 3. Layer diagram for the proposed CNN model.

- This feature variance is calculated using equation 4 as follows,

$$V_f = \sum \frac{\left(MP - \frac{\sum MP}{N}\right)^2}{N} \tag{4}$$

Where, MP represents the output of max pooling layer, and N represents number of features extracted from the max pooling layer.

- The selected values are then given to a 32x1 convolution layer, followed by the same maximum pooling and drop out layers. Which assists in the estimation of most variant features. A larger window size assists in estimation of more variant ECG features.
- The selected values are then given to a 64x1 convolution layer, followed by the same maximum pooling and drop out layers. Which assist in estimation of most variant features. A larger window size assists in estimation of more variant ECG features.
- The selected values are then given to a 256x1 convolution layer, followed by the same maximum pooling and drop out layers. Which assist in estimation of most variant features. A larger window size assists in estimation of more variant ECG features.
- The extracted features are given to a ReLU based dense correlation layer, which assists in differentiating features of different ECG classes.
- Finally, a fully connected neural network (FCNN) is used to classify different ECG types.

Due to the use of the fuzzy logic layer and the VGG-19 CNN model, the proposed method can improve classification accuracy, reduce the delay needed to classify, and improve precision performance. This can be observed from the next section of this text, wherein performance comparison of different deep learning models for ECG classification is done.

4. Results & comparison

We compared the performance of the proposed modified fuzzy VGGNet-19 model with SVM [1], and recursive CNN (RCNN) [20] models. These models were selected because of similar computational complexity, and scalability when compared with proposed method. Other approaches like the ones mentioned in [8, 10, 21,22] have higher accuracy, but they are deployed on smaller datasets, which limits their applicability, and thus are not used for comparison with this work. This performance is evaluated in terms of average accuracy (A), average precision (P) and delay (D) values. These values are evaluated for different reviewed models, and their results are tabulated in table 1, and 2 wherein it can be observed that the proposed model outperforms other models in terms of accuracy, precision and delay performance. These values were obtained by evaluating the system on MIT-BIH dataset, which consists of over 1000 ECG samples with Premature ventricular contraction, Ventricular escape beat, Paced beat, Ventricular ectopic beat, and Fusion of paced and normal beat. These classes are used in uniform ratios to evaluate the performance of the proposed model, as observed in the following tables.

Table 1. Accuracy of different ECG processing models.

Number of samples	Avg. A SVM	Avg. A RCNN	Avg. A [Proposed]
100	0.68	0.91	0.94
150	0.72	0.91	0.99
200	0.57	0.95	0.99
250	0.59	0.94	0.98
300	0.67	0.86	1.00
350	0.70	0.87	0.99
400	0.73	0.86	0.99
450	0.66	0.86	0.98
500	0.69	0.86	0.97
550	0.70	0.87	0.96
600	0.72	0.87	0.96
700	0.73	0.87	0.96
800	0.74	0.87	0.98
1000	0.74	0.88	0.96
1100	0.73	0.89	0.97
1150	0.74	0.90	0.97
1200	0.74	0.90	0.97
1300	0.74	0.91	0.98
1400	0.75	0.91	0.98
1500	0.75	0.91	0.99
2000	0.76	0.91	0.99

The results showcase that the proposed model is over 8% more accurate than the models in SVM and RCNN, making it useful for real-time deployments. This can also be observed from figure 4, wherein accuracy values are visualized.

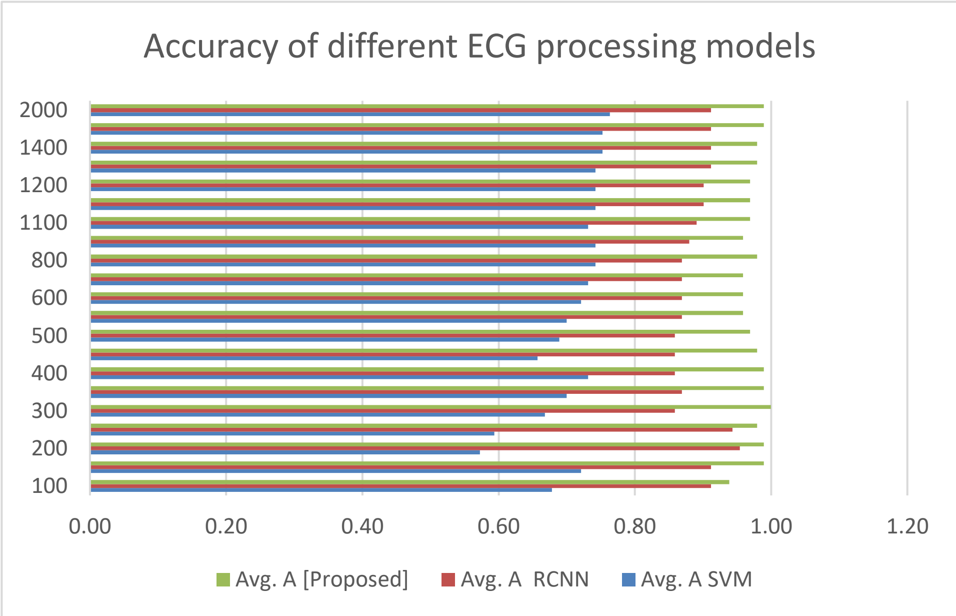

Figure 4. Average accuracy of ECG processing.

Similar analysis is done in terms of precision of processing, and can be observed from Table 2 as follows.

Table 2. Precision of different ECG processing models.

Number of samples	Avg. P SVM	Avg. P RCNN	Avg. P [Proposed]
100	0.71	0.86	0.89
150	0.75	0.86	0.94
200	0.59	0.91	0.94
250	0.62	0.90	0.93
300	0.70	0.81	0.95
350	0.74	0.82	0.94
400	0.75	0.81	0.94
450	0.69	0.81	0.93
500	0.72	0.81	0.92
550	0.74	0.82	0.91
600	0.75	0.82	0.91
700	0.75	0.82	0.91
800	0.76	0.82	0.93
1000	0.77	0.83	0.91

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Table 2. (continued).

1100	0.75	0.84	0.92
1150	0.76	0.85	0.92
1200	0.76	0.85	0.92
1300	0.77	0.86	0.93
1400	0.78	0.86	0.93
1500	0.78	0.87	0.94
2000	0.79	0.87	0.94

The results showcase that the proposed model is over 9% more precise than the models present in SVM and RCNN, thereby making it useful for real time deployments. This can also be observed from Figure 5, wherein precision values are visualized.

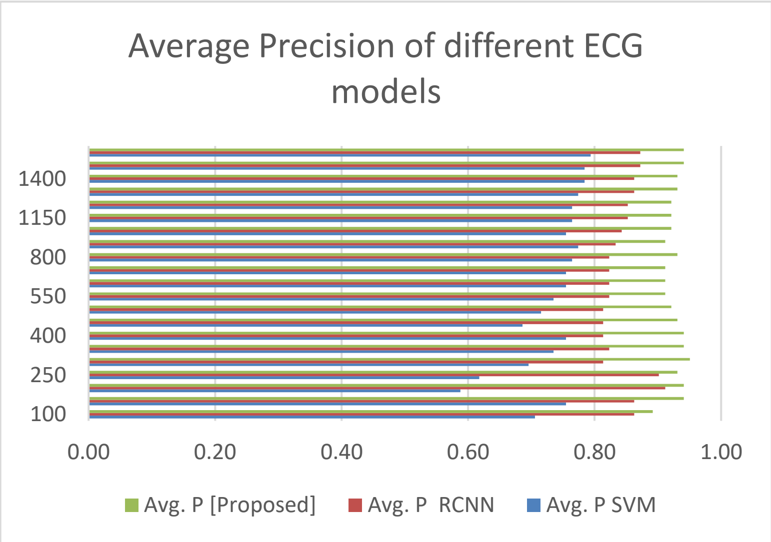

Figure 5. Average precision of ECG processing.

A similar analysis is done in terms of precision of processing and can be observed in Table 3 as follows.

Table 3. Delay of different ECG processing models.

Number of samples	Avg. D (s) SVM	Avg. D (s) RCNN	Avg. D (s) [Proposed]
100	2.32	1.16	1.16
150	1.74	1.16	0.58
200	3.86	0.58	0.58
250	3.48	0.69	0.69
300	2.48	1.74	0.46
350	1.94	1.67	0.61
400	1.58	1.68	0.61

Table 3. (continued).

450	2.53	1.73	0.66
500	2.21	1.71	0.78
550	1.96	1.68	0.89
600	1.76	1.62	0.94
700	1.60	1.60	0.97
800	1.46	1.58	0.72
1000	1.34	1.46	0.87
1100	1.66	1.35	0.86
1150	1.55	1.29	0.81
1200	1.45	1.23	0.77
1300	1.36	1.18	0.72
1400	1.29	1.12	0.67
1500	1.22	1.09	0.62
2000	1.17	1.01	0.56

From the delay values it is evident that the proposed Modified VGGNET-19 model outperforms other models, and achieves 25% improvement in speed. This can also be observed from figure 6, wherein these values are visualized. These results show that the proposed model is highly applicable for real-time ECG processing applications.

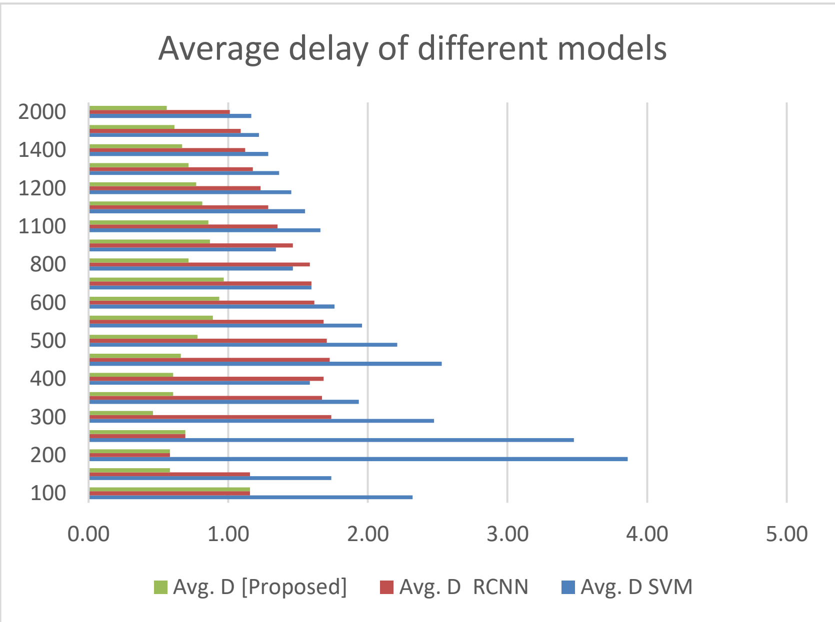

Figure 6. Average delay for different models.

5. Conclusion and future work

After testing the proposed system on over 1000 samples, it is evident that the Modified fuzzy VGGNET-19 classification engine can optimize ECG processing performance. Furthermore, it is observed that the

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proposed model is over 15% more effective than state-of-the-art techniques, and has 22% lower delay as well. These metrics make the system model perform better and more sophisticated when applied to large datasets. In future, researchers can apply LSTM and other models and check their performance on the proposed ECG processing application.

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