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A Kohonen Self Organizing Map (KSOM) Technique for Classification of Electrocardiogram (ECG) Signals

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ABSTRACT
Electrocardiogram (ECG) signals are crucial in diagnosing cardiovascular diseases. Handling noisy ECG data, which is common in real-world situations makes accurate classification a critical task. Because ECG signals are faint and are quickly disrupted, classification accuracy can be poor, hence the need for improvement in the automatic ECG categorization system's recognition accuracy. The Kohonen Self Organising Map (KSOM) is known for its ability to cluster high-dimensional data in a low-dimensional space, hence its adoption in this research. The procedure employed include collection and pre-processing of diverse ECG data, including normal and abnormal cardiac rhythms. Inherent noise was removed from the data to ensure better-quality input data into the classification algorithm. A Kohonen SOM neural network (MiniSom model) was trained using the preprocessed ECG data. The KSOM organizes ECG signals into clusters on a topological map, preserving similarities and dissimilarities between different cardiac rhythms. Subsequently, the trained SOM serves as a reference model for classifying unseen ECG signals, indicating the corresponding cardiac rhythm. Benchmarked on two different dataset, evaluation of the classification performance of the technique was carried out. Cross-validation was done to assess the model's robustness and generalizability. Comparative analysis was conducted to measure the effectiveness and efficiency of the SOM-based approach against other common ECG signal classification techniques based on accuracy, precision, recall and fi-score. The result obtained shows that the average accuracy of 94.2%, precision of 83%, recall of 100% and f1-score of 91% achieved by the MiniSOM model outperformed the other models.

Key words: self-organizing map, cardiac rhythm, classification, electrocardiogram.

1. INTRODUCTION

The electrical signal from the heart is recorded by an electrocardiogram, or EKG, which is used to screen for various cardiac problems. The electrical impulses that cause the heart to beat are recorded using electrodes applied to the chest. The signals appear on a connected computer as waves. The analysis and processing of ECG signals are key approaches in the diagnosis of cardiovascular diseases (Duong et al., 2023; Śmigiel et al., 2021). The main field of work in this area is classification, which is increasingly supported by machine learning-based algorithms (Śmigiel et al., 2021). Electrocardiography (ECG) is a medical test that detects cardiac abnormalities by measuring the electrical activity generated by the heart. The heart produces tiny electrical impulses that spread through the heart muscles. These impulses can be detected using an ECG machine. An ECG machine records the electrical activity of the heart and displays these data as a trace on paper (Prashar et al., 2020). The data will then be interpreted by a medical practitioner. ECG helps identify the cause of symptoms or chest pain and detect abnormal heart rhythm or cardiac (heart) abnormalities. ECGs from healthy hearts had characteristic shapes. Any irregularity in the heart rhythm or damage to the heart muscles can change the electrical activity of the heart; thus, the shape of the ECG changes (Zhu et al., 2021). A doctor may recommend an ECG for patients who are at risk of heart disease because of a family history of heart disease, smoking, overweight, diabetes, high cholesterol, or high blood pressure.

ECG classification problem is very important and have received strong attention from not only medical community but also community of computer scientists especially from AI field. Heart disorders that can be detected using ECG include abnormal heart rhythms, heart attacks, and an enlarged heart. Owing to the high mortality rate of persons with heart diseases, early detection and precise discrimination of ECG signals are essential for the treatment of patients. The early and accurate detection of ECG arrhythmia can assist doctors detect various heart diseases (Saini & Gupta, 2022). Classification of ECG signals using machine learning techniques can provide substantial input for doctors to confirm the diagnosis. Researchers have explored various deep learning architectures for ECG classification, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and their combinations like Convolutional Recurrent Neural Networks (CRNNs). CNNs are effective in capturing spatial patterns in the ECG waveform, while RNNs excel at modeling temporal dependencies. By combining these architectures in CRNNs, researchers have achieved improved accuracy in ECG classification tasks. However, CNNs also have certain shortcomings that restrict how well they work and how widely they may be used. CNNs' primary drawback is that, in order to train efficiently, they need a lot of labeled data, which can be expensive and time-consuming to collect and annotate.

The main objective of this research is to classify ECG signals into normal and abnormal ones using the miniSOM variant of Kohonen Self-Organizing feature map. Self-Organizing feature map (SOM) refers to a neural network, which is trained using competitive learning. Basic competitive learning implies that the competition process takes place before the cycle of learning. The competition process suggests that some criteria select a winning processing element. After the winning processing element is selected, its weight vector is adjusted according to the used learning law (Kohonen, 1990).

The self-organizing map makes topologically ordered mappings between input data and processing elements of the map. The self-organizing map refers to an unsupervised learning model proposed for applications in which maintaining a topology between input and output spaces is required. The notable attribute of this algorithm is that the input vectors that are close and similar in high dimensional space are also mapped to close by nodes in the 2D space. It is fundamentally a method for dimensionality reduction, as it maps high-dimension inputs to a low dimensional discretized representation and preserves the basic structure of its input space.

All the entire learning process occurs without supervision because the nodes are self-organizing. They are also known as feature maps, as they are basically retraining the features of the input data, and simply grouping themselves as indicated by the similarity between each other. It has practical value for visualizing complex or huge quantities of high dimensional data and showing the relationship between them into a low, usually two-dimensional field to check whether the given unlabeled data have any structure related to it.

This research develop and implement a self-organizing neural network (SOM) for the classification of ECG signals. It categorize various types of ECG abnormalities and normal patterns, providing a robust and interpretable ECG classification system. The research seeks to explore the application of SOMs in medical signal analysis, contributing to the advancement of ECG classification methods and offering healthcare professionals an effective tool for early detection and precise identification of this cardiovascular disease. The rest of this paper is arranged as follows; section 2 discussed related research work while section 3 presents the materials and methods. Section 4 explains the experimental setup and section 5 discussed the results of the experiment. The conclusion and recommendation is presented in section 6.

2. RELATED WORK

Accurate classification of ECG signals can assist in the early detection and diagnosis of some heart-related conditions, including Arrhythmias and heart diseases as stated in (Saini & Gupta, 2022) and (Zhu et al., 2021). The literature amass positive research outputs in this domain. In (Tang et al., 2022), the authors proposed a robust reconstruction of electrocardiogram using photoplethysmography (PPG). The work recommended that PPG can be used to reconstruct the ECG, hence practitioners can gain deep understanding of the patient's cardiovascular health using the signals. A bidirectional long short-term memory (BILSTM) model was trained and validated for 1minue to generate 3-8 min ECG signal. Filtering, alignment, normalization, dataset splitting and segmentation was done. The result suggested that further research is required especially when the r-value obtained was low. A python-based toolbox was proposed in (Kramer et al., 2022) to access ECG lead signals quality used to develop an efficient model in near-real-time on a mobile phone. Stationary signal check, Heart rate check and Signal-to-noise ratio check was realized with the system. A large percentage of the signals were correctly categorized as acceptable or unacceptable.

An Imbalanced ECG signal-based heart disease classification using ensemble machine learning technique was developed in (Rath et al., 2022). 1,024 samples of ECG signals were considered. The work used of AdaBoost algorithm, Logistic regression, Support vector machine, LR-AdaBoost ensemble model. The result of the performance comparison reveals that the AdaBoost perform better than the SVM, LR-based classification models. In (Wu et al., 2021), the authors proposed a study on Arrhythmia via ECG Signal Classification Using the Convolutional Neutral Network. The proposed CNN network uses the average -pooling layer instead of the max-pooling layer. This approach has a better performance in accuracy, sensitivity, robustness, and anti-noise capability. (Sahoo et al., 2022) proposed a deep learning-based system to predict cardiac arrhythmia using hybrid features of transform techniques. The work tried to address the problem of manual screening of the electrocardiogram (ECG) signals which is time consuming, strenuous, and liable to human errors. The work carried out denoising, detection of peaks, features extraction and classification. The result of the experiment has a comparable performance with the existing similar work.

(Chiang et al., 2019), proposed a system for noise reduction and low signal distortion in ECG signals. This was achieved by the use of denoising autoencoder (DAE) and Fully Convolutional Network (FCN). The experimental results showed that FCN outperforms DNN and CNN, with DNN having the worst performance, more specifically the QRS complexes are not well reconstructed by DNN, leading to loss of clinical information. In (Cheng et al., 2021), a new method for automatic identification and classification of ECG signals was developed. The work uses a dense heart rhythm network that combines a 24-layer Deep Convolutional Neural Network (DCNN) and Bidirectional Long Short-Term Memory (BiLSTM) to deeply mine the hierarchical and time-sensitive features of ECG data. The experiment produced an accuracy of 0.893, and its F1 score is 0.891. (Chen et al., 2022) develop an automated spatio-temporal learning-based Sino Atrial (SA) detection method. In the work, the respiratory rate (RR) intervals and R-peak amplitudes were extracted from combining adjacent and labeled segments and were fed into the proposed CNN bi-directional gated recurrent unit (CNN-BiGRU) model. The model achieved an accuracy of 91.22% In (Fang et al., 2022), an automatic ECG analysis for diagnosis of heart disease based on radial basis function (RBF) Neural Network technology was developed. The technique was benchmarked on the Massachusetts Institute of Technology Beth Israel Hospital (MIT-BIH) ECG database. It extract the QRS features of ECG signals using the Pan-Tompkins algorithm. Then K -means clustering was used to screen the samples and RBF neural network was used to analyze the ECG information. The comprehensive test results shows that the detection accuracy of normal ECG signals was 99.74%, the detection of abnormal ECG signals was 97.53%.

(Hurr et al., 2022) proposed an approach to develop a convolutional neural network-based extraction technique for human physiological signal features and uses an MPL classifier to detect whether the ECG signal is normal or not. Using wavelet transform and morphological filtering for preprocessing, the result concludes that the method has good detection performance with sensitivity of 99.54%, positive prediction rate PPR of 99.65%, detecting error ratio (DER) of 0.35% and accuracy of 99.55%. However, the speed of classification was a major limitation of the work. (Ma et al., 2022) proposes a deep learning algorithm for automated ECG-based arrhythmia detection. The work uses generative adversarial networks to augment sparse data, and a spatial and temporal information fusion model based on ResNet and BiLSTM were used to identify different types of arrhythmias in long-term ECG. The proposed technique improves arrhythmia diagnostic accuracy by 99.4%, demonstrating high recognition performance. In (Wu et al., 2022) a deep neural network ensemble classifier with focal loss was developed for automated arrhythmia classification. The work uses a new heartbeat segmentation method, by employing a combination of traditional sampling and focal loss, and a deep CNN ensemble classifier for classification validation. The results show an overall accuracy of 91.89%, sensitivity of 85.37%, positive productivity of 59.51%, and specificity of 93.15%. (Dhar et al., 2021) developed a cross-wavelet assisted convolution neural network (AlexNet) approach for phonocardiogram (PCG) signals classification. The combination of CNN and AlexNet was able to detect abnormal heart sounds, which are symbols of cardiovascular disease. The method was applied to both raw and de-noised PCG data, and achieved an accuracy of 98% and 97.89% respectively.

3. MATERIALS AND METHODS

In this research, the classification of ECG signal was done following the procedure presented in this section. The system design initiates with data acquisition from a public repository and ends with model comparison. The basic pattern of this electrical activity comprises three waves, which have been named P, QRS (a wave complex), and T. A sample of typical normal and abnormal ECG signal is shown in figure 1 and figure 2 respectively.

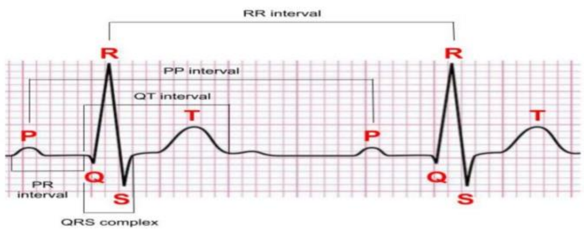


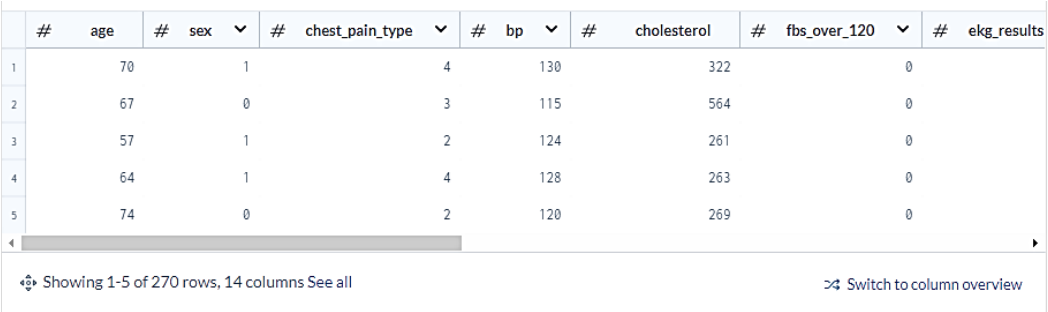
Figure 1: Normal ECG signal (Li & Boulanger, 2020)

Figure 2: Abnormal ECG signals (Li & Boulanger, 2020)

3.1 Data Acquisition and Preprocessing

In this research, two datasets (simulate and real-world) from Kaggle and data.world were acquired for use. These datasets contain a comprehensive collection of clinical records that are related to ECG signals. The two datasets were acquired from data.world and Kaggle with the links https://data.world/informatics-edu/heart-disease-prediction for the simulate dataset and https://www.kaggle.com/datasets/taejoongyoon/mitbit-arrhythmia-database for the real-world dataset. The simulate dataset contains 270 rows and 14 columns, while the real world dataset (combination of the mitbih_test, mitbih_train, ptbdb_abnormal, and ptbdb_normal datasets of the MIT-BIH Arrythmia database) on the other hand, contains a total of 123998 rows and 188 columns. A sample of the first few rows and columns of the dataset is shown in figure 3. The acquired datasets were preprocessed to ensure their quality and suitability for the subsequent analysis. The following key preprocessing procedures were carried out;

i. Importing the libraries: Libraries such as numpy, pandas, matplotlib and seaborn, minisom and tensorflow were imported to allow data manipulation, visualization, and modeling.
ii. Loading the datasets: The two datasets the simulate dataset, and the real-world dataset, containing four datasets, were imported.
iii. Handling missing data: Duplicate entries were eliminated to avoid biases in the analysis process and improve the data reliability.
iv. Label encoding: Label encoding was performed to convert categorical data and or text-based data into numerical values.
v. Feature Normalization: Feature normalization was performed for adequate and consistent scaling of the data.



	# age	# sex	# chest_pain_type	# bp	# cholesterol	# fbs_over_120	# ekg_results
1	70	1	4	130	322	0	
2	67	0	3	115	564	0	
3	57	1	2	124	261	0	
4	64	1	4	128	263	0	
5	74	0	2	120	269	0	

Showing 1-5 of 270 rows, 14 columns See all
Switch to column overview

Figure 3: Sample of the ECG dataset features

3.2 Model Training

The basic idea behind a Self-Organizing Map is to create a low-dimensional representation of high-dimensional data while preserving the topological relationships between data points. Amidst the varieties of Python libraries and implementations of self-organizing map which include MiniSom, SOMPY, SOM-Toolbox, Neurolab, MiniSom was implemented in this research due to its simplicity and ease of interpretation of result. The procedure for the MiniSom implementation is presented below;

i. **SOM Initialization**: initializes the SOM's grid of neurons using random values or a custom initialization scheme.
ii. **Training**: The training process involves finding the best-matching unit (BMU) for each input data point and updating the weights of the BMU and its neighbors.
iii. **Learning Rate and Neighborhood Radius**: tuning this parameter for gradual reduction of the learning rate and the neighborhood radius over time, to allow convergence.
iv. **Customizable Grid**: defining the grid's dimensions, rows and columns, to control the structure of the SOM.
v. **Distance Metrics**: Euclidean distance or cosine similarity used to determine the similarity between input data and neurons.
vi. **Visualization**: visualize the trained SOM using U-matrix, to show the distances between neurons, and the component planes, which display the weight vectors of neurons.
vii. **Saving and Loading**: for further analysis or visualization.
viii. **Quantization**: using the SOM to quantize input data and mapping of data points to the nearest neurons on the map.

The algorithm is detailed below.

Algorithm 1. MiniSOM: (Mnishko & Rauber, 2022)
Begin
1. Initialization. (Each node weight initialize to a random value)
2. Choose a random input vector

3. Calculate the Euclidean distance between weight vector wij and the input vector x(t) connected with the first node, where t, i, j =0.
4. Track the node that generates the smallest distance t.
5. Calculate the overall Best Matching Unit (BMU). It means the node with the smallest distance from all calculated ones.
6. Discover the topological neighbourhood βij(t) and its radius σ(t) of BMU in the Kohonen Map.
7. Repeat for all nodes in the BMU neighbourhood: Update the weight vector w_ij of the first node in the neighbourhood of the BMU by including a fraction of the difference between the input vector x(t) and the weight w(t) of the neuron.
8. Repeat the complete iteration until reaching the selected iteration limit t=n.
End

Where
t = current iteration.
i = row coordinate of the nodes grid.
J = column coordinate of the nodes grid.
W= weight vector
w_ij = association weight between the nodes i,j in the grid.
X = input vector
X(t)= the input vector instance at iteration t
β_ij = the neighbourhood function, decreasing and representing node i,j distance from the BMU.
σ(t) = The radius of the neighbourhood function, which calculates how far neighbour nodes are examined in the 2D grid when updating vectors which gradually decreases over time.

The preprocessed datasets were used to train the MiniSom model. During the training process, the hyperparameters of the model, such as the sigma and learning rate, were manually tuned to optimize performance. The model was trained on the training set (the abnormal and normal datasets for the real-world dataset), which aimed to learn the patterns and relationships within the data that can aid in the classification of ECG signals.

3.3 Model Performance Evaluation

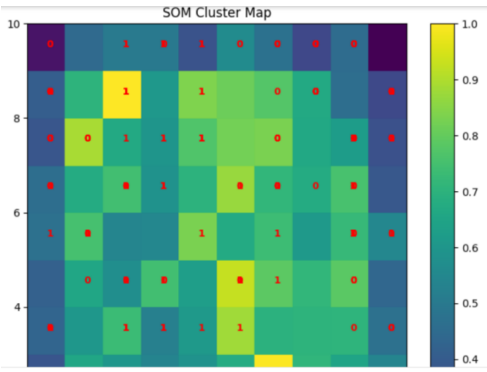
After training the model, it was evaluated using the testing set, which comprised the remaining portion of the preprocessed data that was not used during training. The evaluation involved classifying ECG signals status of the samples in the test set and comparing the classification reports with the target. The following classification metrics were computed; accuracy, precision, recall and f1score.

3.4 Experimental Analysis

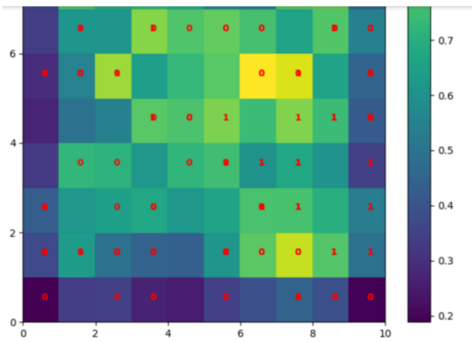
The result was classified in binary form Class 0 and Class 1 for the simulated dataset, and from Class 0 to Class 4 for the real-world dataset.

3.4.1 The Simulated Dataset

In the case of the simulated dataset, Class 0 implies the absence of heart disease while Class 1 implies the presence of heart disease. In the case of the real-world dataset, Class 0 implies the majority class of ECG signals while from Class 1 to Class 4 represents the minority classes of ECG signals. The head of the DataFrame shows the first few rows of the data, including columns such as age, sex, chest pain type, blood pressure (BP), cholesterol levels, fasting blood sugar (FBS) status, EKG results, maximum heart rate (Max HR), exercise-induced angina, ST depression, slope of ST, the number of vessels fluoroscopy, thallium test results, and the presence or absence of heart disease. The tail of the DataFrame shows the last few rows of the data, providing a comprehensive view of the dataset. Removing outliers is a preprocessing step that was carried out to improve the quality of the dataset by eliminating extreme values that could disproportionately influence analysis. The MiniSom model was trained using 4 steps of cross validation and the visualization of its cluster maps is shown in Figure 4a, 4b, 4c, 4d and 4e respectively.

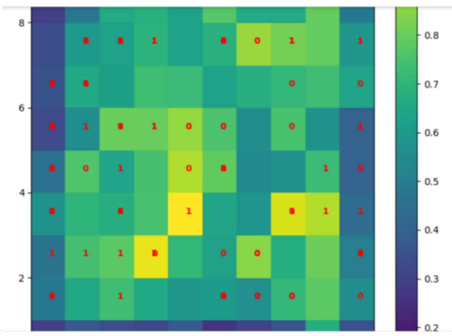


4(a)

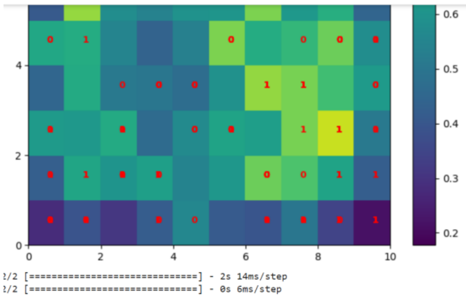


4(b)

4(c)



4(d



4(e)

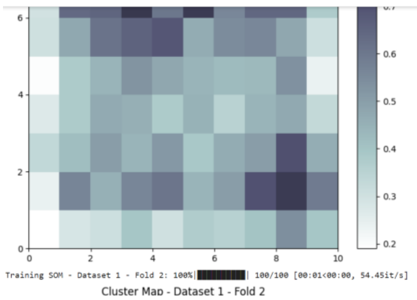
Figure 4(a-e): SOM under 5 splits of Cross-Validation for Simulate Dataset.

As shown in figure 1 above, the output represent the training and evaluation of the Self-Organizing Map (SOM) model using a 5-fold cross-validation technique (StratifiedKFold). The output suggests that the SOM model is being trained and evaluated iteratively for each fold of the cross-validation. The specific steps performed in each iteration include training the SOM on one part of the data (training set) and evaluating its performance on another part (validation). The times shown indicate the computational time required for these operations.

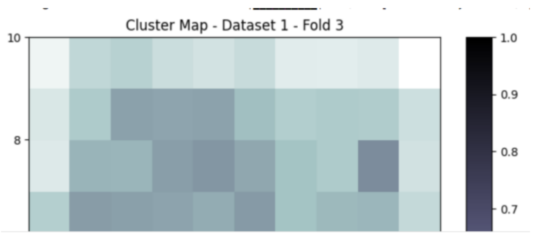
3.4.2 The Real-World Dataset

The three real world datasets (mitbih_train, ptbdb_abnormal, and ptbdb_normal) was normalized and denoising was done using Median Filtering. The values after normalization range between 0 and 1, indicating that the data has been scaled to a common range for consistent processing. Overall, these preprocessing steps indicate that the dataset has been cleaned, denoised, and prepared for analysis. Figure 5a- 5e, Figure 6a – 6e and Figure 7a – 7e depicts the cross validation steps of training and as well evaluating the MiniSom model and visualization of its cluster maps respectively.

5(a)



5(b)



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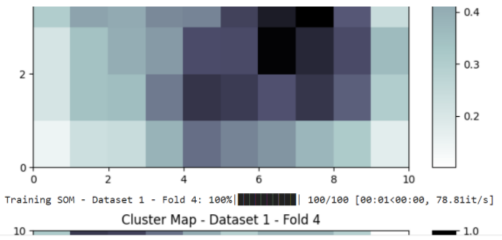

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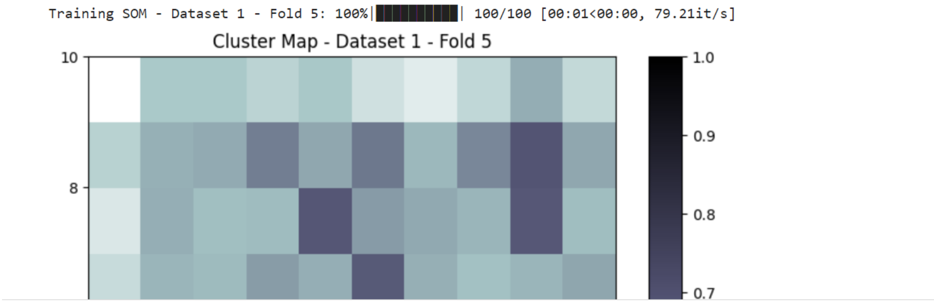
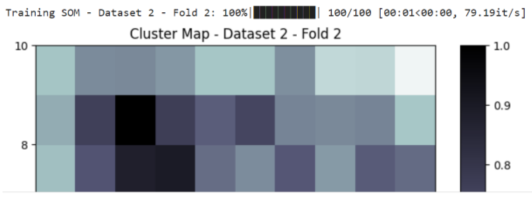


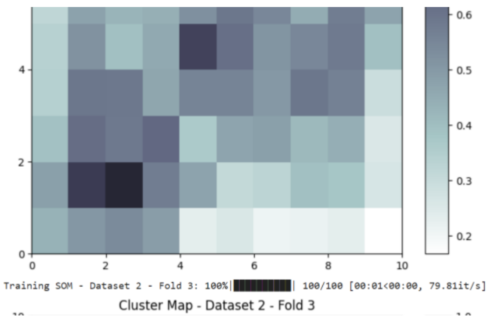
5(e)

Figure 5(a-e): SOM under 5 splits of Cross-Validation for mitbih_train dataset

6(a)



6(b)



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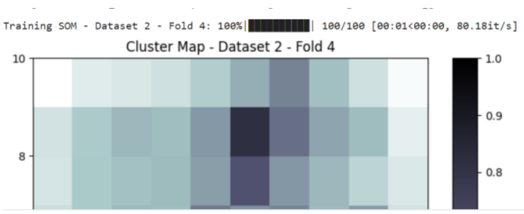

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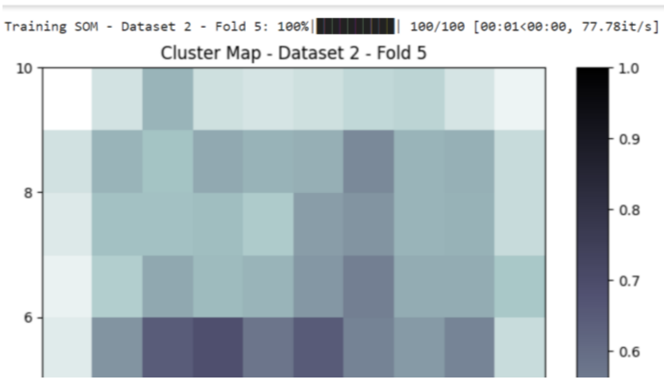
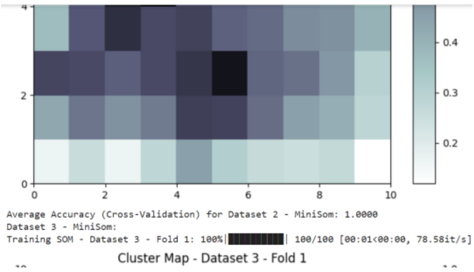
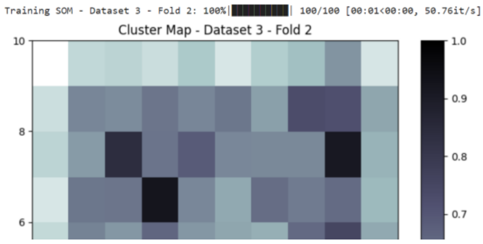


6(e)

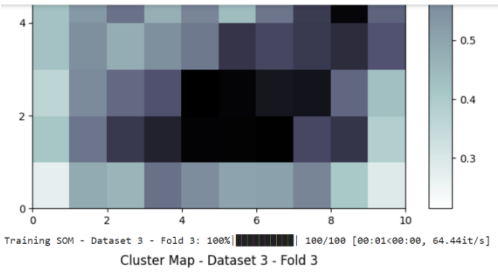
Figure 6(a-e): SOM under 5 splits of Cross-Validation for ptbdb_abnormal



7(a)



7(b)



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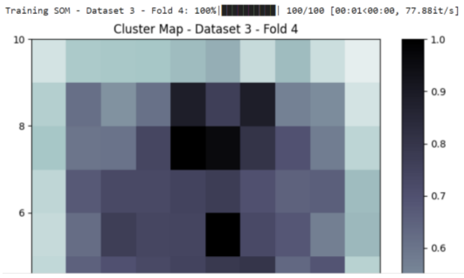
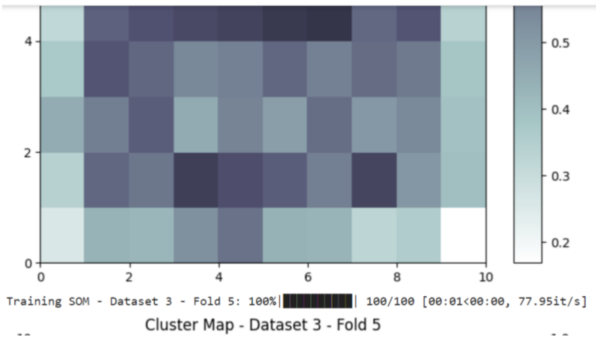


7(d)



7(e)

Figure 7(a-e): SOM under 5 splits of Cross-Validation for ptbdb_normal

As shown in figures 5(a-e), 6(a-e) and 7(a-e) above, the results of training Self-Organizing Maps (SOM) on the three different real world datasets using 5 splits of stratified k-fold cross-validation shows that: The average accuracy (cross-validation) achieved for dataset-1 using MiniSom was approximately 93%. The average accuracy (cross-validation) achieved for dataset-2 using MiniSom was 100%, indicating perfect accuracy. Dataset-3 also achieved an average accuracy of 100%, indicating perfect accuracy. Hence, it can be observed that MiniSom performed exceptionally well on Dataset-2 and Dataset-3, achieving perfect accuracy during cross-validation. However, for Dataset 1, it achieved a lower but still reasonable average accuracy of approximately 93%. These results suggest that MiniSom effectively captured the underlying patterns in the data, with Dataset 2 and Dataset 3 being particularly well-suited for this type of analysis.

4. RESULTS AND DISCUSSION

The result of the experiment carried out in this research on the simulated dataset as well as the real world datasets is presented in this section. The result achieved using MiniSOM was compared to some state of the art machine learning techniques (RNN, ANN, and Random Forest) which were benchmarked on the same datasets using the performance evaluation metrics are presented.

4.1 Performance of Simulated dataset

As shown in Table 1a and 1b for the simulated dataset, it can be observed that Precision, Recall, and F1-score values for class 0 (the "Absence" class) are reasonable, with relatively high precision and recall. Class 1 (the "Presence" class) has slightly lower precision and recall, indicating some misclassification. Overall accuracy is 93% and 92% respectively, with a balanced macro-average F1-score.

Table 1a: Model Performance Comparison for Class 0.

MODEL	ACCURACY	PRECISION	RECALL	F1-SCORE
MiniSom	93%	88%	90%	84%
RNN	62%	62%	87%	72%
ANN	79%	79%	80%	73%
Random Forest	81%	83%	82%	81%

Table 1b: Model Performance Comparison for class 1.

MODEL	ACCURACY	PRECISION	RECALL	F1-SCORE
MiniSom	92%	83%	68%	76%
RNN	62%	60%	27%	38%
ANN	79%	74%	56%	72%
Random Forest	81%	75%	77%	63%

From Table 1b, Class 1 (the "Presence" class) has slightly lower precision and recall, indicating some misclassification. From both tables, the MiniSOM model achieves the highest overall accuracy of 93% and has the highest macro-average F1-score among the models. These reports provide insights into the models' capabilities in correctly classifying instances into their respective classes.

4.2 Performance of real-world dataset

For the real-world datasets, the MiniSom model achieved an average accuracy of approximately 94.2% on the test set, which is the ratio of correctly classified instances to the total number of instances. These is presented in Table 2a, 2b, 2c, 2d and 2e. The precision, recall, and F1-score for Class 0.0 are relatively high, indicating that the model performs well in correctly classifying instances belonging to this class.

However, for all other classes (Class 1.0, Class 2.0, Class 3.0, and Class 4.0), the precision, recall, and F1-scores are all extremely low (with mostly 0%). This suggests that the model struggles to correctly classify instances into these classes, resulting in very poor performance. In summary, the MiniSom model achieved a relatively high accuracy, primarily driven by its ability to classify instances into Class 0.0. However, it struggled significantly with the other classes, resulting in very poor precision, recall, and F1-scores for those classes.

Table 2a: Model Performance Comparison for Class 0.

MODEL	ACCURACY	PRECISION	RECALL	F1-SCORE
MiniSom	94.2%	83%	100%	91%
ANN	83%	83%	100%	91%
RNN	63%	61%	81%	72%
Random Forest	83%	83%	100%	91%

Table 2b: Model Performance Comparison for Class 1.

MODEL	ACCURACY	PRECISION	RECALL	F1-SCORE
MiniSom	94.2%	0%	0%	0%
ANN	83%	0%	0%	0%
RNN	60%	59%	71%	82%
Random Forest	83%	0%	0%	0%

Table 2c: Model Performance Comparison for Class 2.

MODEL	ACCURACY	PRECISION	RECALL	F1-SCORE
MiniSom	94.2%	0%	0%	0%
ANN	83%	0%	0%	0%
RNN	61%	64%	81%	62%
Random Forest	83%	0%	0%	0%

Table 2d: Model Performance Comparison for Class 3.

MODEL	ACCURACY	PRECISION	RECALL	F1-SCORE
MiniSom	94.2%	0%	0%	0%
ANN	83%	0%	0%	0%
RNN	69%	60%	67%	71%
Random Forest	83%	0%	0%	0%

Table 2e: Model Performance Comparison for Class 4.

MODEL	ACCURACY	PRECISION	RECALL	F1-SCORE
MiniSom	94.2%	0%	0%	0%

ANN	83%	0%	0%	0%
RNN	60%	52%	77%	62%
Random Forest	83%	0%	0%	0%

From the tables, it was observed that the classification reports for the different models on the test dataset share several common characteristics, in terms of values of precision, recall and f1-score. The average accuracy of 94.2% for the MiniSOM model outperformed the other models. ANN and Random Forest models achieved the same accuracy of approximately 83% on the test set. For all models, the precision, recall, and F1-score for most classes (Class 1.0, Class 2.0, Class 3.0, and Class 4.0) are very low or zero. This suggests that these models struggled to correctly classify instances into these classes. In contrast, the precision, recall, and F1-score for Class 1.0 are not available (indicated as 0.00) for most of the models, because this class may not have been correctly predicted by the models at all.

5. CONCLUSION AND FUTURE WORK

This work developed a system for classification of ECG signals using MiniSOM model. The system was benchmarked on two datasets acquired from online repositories. The performance of the system was compared to some state of the art machine learning models. The result of the evaluation shows that the proposed model outperformed the existing systems based on the evaluation metrics considered. The developed system, driven by the Kohonen Self-Organizing Neural Network, exhibited promising capabilities in automated arrhythmia ECG classification. However, the support column in the classification report represents the number of instances in each class. Class 0.0 has a significantly higher support value of 18,118 compared to other classes, indicating a severe class imbalance issue in the dataset. Therefore, the research will be taken further by exploring various technique of balancing of dataset to address the challenge of class imbalance inherent in the real world datasets. Also, combination of deep learning models for improved performance of classification will be looked into.

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