DESIGN OF A HIGH-PERFORMANCE ECG CLASSIFICATION MODEL USING HYBRID GENETIC MACHINE LEARNING MODEL (GM2LH)

[1]PRAKASH CHANDRA SAHOO*, [2]BINOD KUMAR PATTANAYAK, [3]RAJANI KANTA MOHANTY, [4]BIBHUPRASAD MOHANTY

[1]: Department of Computer Science and Engineering, Institute of Technical Education and Research, Siksha 'O' Anusandhan Deemed to be University, Bhubaneswar, Odisha, India, Email: prakashsahooresearch2019@gmail.com

[2]: Department of Computer Science and Engineering, Institute of Technical Education and Research, Siksha 'O' Anusandhan Deemed to be University, Bhubaneswar, Odisha, India,

[3]:Department of Computer Science and Engineering-SP, Jain Deemed to be University, Bengaluru, Karnataka, India,

[4]: Department of Electronics and Communication Engineering, Institute of Technical Education and Research, Siksha 'O' Anusandhan Deemed to be University, Bhubaneswar, Odisha, India,

Email: binodpattanayak@soa.ac.in, rkm.bbs@gmail.com, bibhumohanty@soa.ac.in

*: Corresponding Author

ABSTRACT

Categorization of electro-cardiogram (ECG) is a primary task for any heart disease classification application. A wide variety of signal processing models are needed in order to perform this task, this includes pre-filtering, noise removal, extraction of features, selection of features, categorization and temporal analysis. Designing a high efficiency ECG classification model requires development & testing of individual methods, and their integration via machine learning models. During integration of these models, inefficiencies are introduced into the system, which reduces final classification accuracy. These efficiencies include, but are not limited to, signal interface between different blocks, classifier feedback, feature selection sizing inefficiency, etc. In order to remove these drawbacks, a novel hybrid Genetic Machine Learning Model (GM2LH) classifier is proposed in this text. Due to an integrated approach taken by the classifier, it is able to classify datasets taken from Massachusetts Institute of Technology-Beth Israel Hospital (MIT-BIH) with 99.7% accuracy, 99.48% precision, 99.15% recall and 99.2% fMeasure performance. The proposed GM2LH model combines feature extraction, feature selection, categorization, and feedback steps into a single integrated approach, which reduces dependency on decentralized blocks. Comparison with state-of-the-art models showcases superiority of proposed GM2LH model, and confirms its utility for different kind of heart diseases. The proposed GM2LH model both enhances classification accuracy and ensures robust feature selection and extraction, making it a promising solution for real-time ECG analysis and early detection of cardiovascular diseases

Keywords: *Electrocardiogram (ECG), Massachusetts Institute Of Technology-Beth Israel Hospital (MIT-BIH), Arrhythmia, Categorization, Genetic Model, Hybrid, Feature Extraction*

1. INTRODUCTION

Electrocardiogram (ECG) grouping is a multidomain task which requires productive plan of an assortment of sign handling blocks. These squares incorporate, yet are not restricted to, ECG obtaining, pre-handling, separating, highlight extraction, include choice, grouping and post-handling. Because of headway in signal procurement innovation, and coordination of on-board advanced signal handling (DSP) components, the sign securing and sifting processes are as of now enhanced for ECG signals, yet the other handling units like element extraction, include choice, grouping and post-handling should be performed with high precision to foster a profoundly compelling ECG characterization framework. Association between these squares can be seen from figure 1, wherein the QRS highlight is utilized for

Journal of Theoretical and Applied Information Technology
28th February 2025. Vol.103. No.4

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

arrangement of ECG signals into typical and arrythmia signals. Every ECG wave is fundamentally comprised of P-Wave, which is the underlying flood of the ECG signal. It is a low abundancy, and brief time frame period wave that has an average timespan to 0.22 seconds for standard heart beat designs. QRS wave, which is otherwise called the heartbeat, is a spike-like wave with a normal span of under 0.12 seconds. Distinction between 'R' spans for 2 successive ECG signals is named as 'RR' stretch, and is utilized for recognizable proof of arrhythmic heart signals. ST fragment, which is utilized for estimating melancholy in practice pressure testing. QT length, is otherwise called the span of a beat, covers the spike and the resting rushes of ECG. It has an average span of under 0.47 seconds for females, and 0.45 seconds for guys.

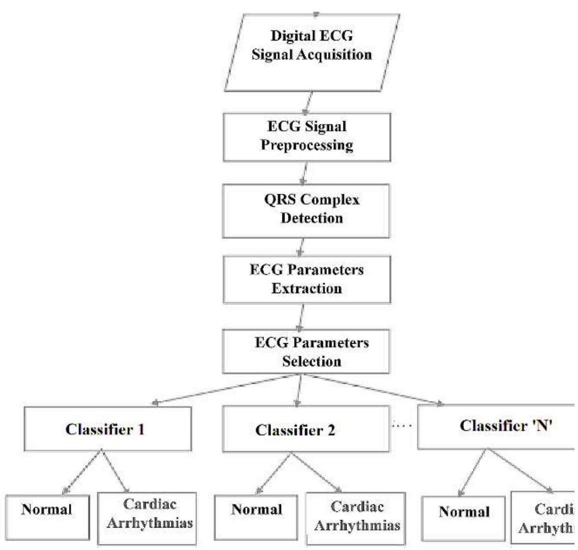

Figure 1. A typical ECG classification system

This multitude of waveforms and more can be utilized for highlight extraction for any ECG signal. When the elements are extricated, then, at that point, they are given to a component choice unit. Here relying on the component difference, a few highlights are eliminated while others are passed on for grouping purposes. The primary models of element determination unit is that contrast between elements of same coronary illness classification should be basically as low as could really be expected, while distinction between highlights of various coronary illness classification should be all around as high as could really be expected. These chose highlights with greatest difference are given to an order block, which utilizations models like brain organizations, support vector machines, arbitrary woodlands, convolutional brain organizations, and so on to separate between signals having a place with various classifications. The consequences of this arrangement are given to a post-handling block, which can break down design changes in these signs, and assess future wellbeing gambles for patients. Countless calculations are proposed to play out these undertakings, a study of the most as of late proposed calculations can be seen from the following area. This will permit specialists to assess subtleties, benefits and downsides of these frameworks. It is trailed by plan of CNN with bio-motivated and straight order calculations like irregular woodland, kNN and SVC. This research aims to bridge the gap between efficiency and accuracy in ECG classification by introducing a hybrid machine learning approach that integrates deep learning with evolutionary algorithms to optimize feature selection and classification performance.

At last, this text finishes up with execution examination of the proposed calculation and its correlation with a portion of the great proficiency explored models for ECG grouping; and furthermore, prescribes future exploration toward this path to additionally streamline in general framework execution.

2. LITERATURE REVIEW

To upgrade the presentation of ECG signal characterization, countless calculations have been proposed by scientists throughout the course of recent years. The vast majority of these calculations utilize brain organizations and other advancement strategies to improve order exactness, accuracy, review and fMeasure values. For example, the work in [1] proposes blend of Convolutional Neural Network (CNN) with Grasshopper Optimization Algorithm (GOA) to get an exactness of 99.58% for the MIT-BIH dataset. This high exactness is gotten by means of the utilization of R-tops and RR-stretches assessed from the wavelet handled ECG signals. Grasshopper improvement calculation is utilized for advanced determination of R-pinnacles and R-R spans, which targets choosing these pinnacles and stretches that have least examining delays. The work in [1] delivers high explicitness and responsiveness values, which makes it helpful for continuous use cases. Another CNN based model that characterizes ECG signals with 98.79% exactness utilizing maximal cross-over wavelet parcel change (MoWPT) and quick pressure leftover convolutional brain organizations

(FCResNet) is proposed in [2]. This model likewise utilizes the standard MIT-BIH dataset for handling. The sign is given to a wavelet change module, wherein unique information signal is changed over into 3 sub-groups, Wide recurrence band (0 to 25 Hz), Low recurrence band (0 to 11.25 Hz), and High recurrence band (11.25 Hz to 22.5 Hz).

To handle these groups, the framework utilizes a blend of quick down-testing based lingering brain network with a quick down-examining convolutional brain network to further develop speed of order. These modules are fell with a lingering convolutional module for high exactness grouping. Because of which a high exactness is accomplished, however this precision is restricted to the given dataset. As dataset changes, the organization must be retrained which causes precision varieties, and subsequently influences framework execution. To keep a reliable exhibition, work in [3] proposes utilization of an exchange learning-based CNN framework that utilizes Icentia 11k dataset for pre-preparing with 98% exactness, and afterward moves this preparing information to one more organization for calibrating that depends on the PhysioNet dataset. It utilizes Contrastive Predictive Coding (CPC) to perform future prescient preparation for moving loads between the pre-preparing and adjusting networks. Exactnesses in the scope of 96% to 98% are accomplished utilizing this cycle, which can be improved by utilizing other high productivity CNN models like GoogLeNet and VGGNet, or through compelling element extraction as recommended in [4], wherein wavelet disintegration is utilized to acquire a precision if 99.58% on the MIT-BIH dataset. The framework involves RR and PR spans as highlights, and joins it with positions and forces of P, Q, R, S, and T sub-waves. This incorporated element vector is given to a brain network-based classifier to perform compelling example acknowledgment, and get high precision levels. The presentation of this reasonably intricate calculation is great, yet isn't tried on ongoing ECG information, which should be done to assess its continuous precision.

A constant order system that utilizes wearable sensor ECG information can be seen in [5]. In this work specialists have consolidated recurrence investigation and Shannon entropy to assess profoundly advanced 24 highlights for heart arrythmia grouping. These highlights are given to irregular woodland, k-closest neighbor, and J48 classifiers, and an exactness between 99.7% is accomplished with DB6 wavelet highlights for 5 unique classes, which diminishes definitely as number of classes increment. For example, the exactness for 6 classes is around 97%, while for 7 classes is 93%, etc. This exactness can be improved through utilization of container networks with CNNs are recommended in [6]. In this work, case networks can consider spatial orders among highlights and rotational change to get a precision of 98.5% for 18 distinct arrythmia classes. These classes incorporate, blood vessel fibrillation, atrial ripple, atrial untimely beat, Bigeminy, Fusion, Idioventricular Rhythm, Left Bundle Branch Block, typical sinus musicality, Outlier, unusual heartbeat rate, Premature ventricular constrictions, Right Bundle Branch Block, Succinate dehydrogenase iron-sulfur subunit mitochondrial, Supraventricular Tachycardia, Trigeminy, Ventricular Flutter, Ventricular Tachycardia and Wolff-Parkinson-White disorder. To acquire such a high precision for countless classes, the model proposes utilization of information expansion, wherein input tests are changed as far as inspecting rate, turn, moving, and so on to make a bigger dataset for preparing. Design of this expand dataset preparing based case organization can be seen from [6], wherein case network is fell with a CNN based decoder network to further develop generally characterization exactness. The underlying square of container network performs reshaping and crushing of ECG signals, which takes into account enormous number of tests to be produced, that are utilized for network preparing by means of case directing layer. All together play out this preparation, a bunch of 'k=3' thick net completely associated (FC) layers are utilized, that take into consideration highlight extraction and choice to accomplish high exactness of arrangement. A comparative high precision CNN model that further develops thick layer execution through utilization of Nadam, Adam, Adadelta and stochastic inclination deterioration (SGD) streamlining agents is proposed in [7]. Because of the proposed enhancement, an exactness of 99.54% is accomplished, which is extremely high and can be utilized for ongoing clinical purposes. ECG signals forces a huge assortment of clamors, which incorporate yet are not restricted to muscle relic, power line commotion, added substance white Gaussian commotion and pattern meander. Separate calculations are required to recognize and eliminate these singular commotion types from the ECG signal, the work in [8] proposes an incorporated system that can diminish the impact of these clamor types with high effectiveness. The system proposes different numerical personalities relying on the provided commotion type to decrease impact of

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

clamor from the ECG information. For example, to eliminate power line obstruction, the work proposes assessment of zero-crossing rate (ZCR) and kurtosis proportion of the information ECG information. Where, 'x' is the ECG signal, 'N' is length of the ECG signal, and HZCRR is high zero-crossing rate proportion. Different assessments are done in basically the same manner, which results into a precision of 99.4% through the utilization of multi-facet perceptron based brain organization. A comparative classifier that utilizations improved molecule swarm advancement (ePSO) calculation with multi-facet perceptron brain organization (MLP-NN) is proposed in [9]. This classifier can accomplish exactnesses in the scope of 99.63% by means of the utilization of 'R' tops, 'QRS' complex division and 'P' and 'T' waves identification. ePSO can likewise be supplanted with outrageous learning machine (ELM) based arrangement models as proposed in [10], wherein Discrete wavelet change with daubechies 1, bior 1.3, bior 3.1 and symlet is utilized for highlight extraction through heart beat deterioration, while ELM with feed-forward brain network is utilized for definite grouping with 98.43% precision. More straightforward classifiers like help vector machines (SVMs) and k-closest neighbors (kNN) can be ensembled with brain networks as recommended in [11] to acquire high exactness levels between 97% to almost 100% across various classes. This high precision is gotten because of a 2-stage highlight extraction module, that consolidates signal denoising, QRS complex and P wave recognition, with abundancy, stretch, term and visual morphological examples for profoundly powerful element portrayal. Stream of this framework can be seen from [12], wherein SVM classifier is demonstrated to be utilized for high precision characterization.

This engineering can order ECG waves into arrythmia classes like supraventricular ectopic beat, ventricular ectopic beat, combination beat, obscure beat and ordinary with high precision. A comparative arrangement model that utilizes 1D CNN can be seen from [12], wherein plan of a versatile CNN is characterized for high productivity order with almost 100% exactness across various datasets. The 1D CNN can be adjusted through the assistance of remuneration balanced spike-timing subordinate versatility (RSTDP) and spike-timing subordinate pliancy (STDP) CNN designs as proposed in [13]. These organizations use the spiking waveform conduct to prepare their inner loads, to diminish power utilization and acquire an order exactness of 98% across 4 arrythmia classes. Generally speaking, engineering of this framework can be seen from [13], wherein blocks like spike encoding, design extraction and grouping should be visible.

The structure utilizes light weight neuron plan, which are explicitly tuned to yield immersed values if there should arise an occurrence of spikes in the info information. Because of this, general power utilization is radically decreased, and the framework can get undeniable degrees of precision with least number of calculations. One more high precision CNN design is characterized in [14] and [15], wherein profound convolution organizations and Residual-Concatenate Network with Metric Learning are proposed. Both these organizations are augmentations of standard CNN design, and add different pooling, softmax and completely associated layers to the first engineering for further developed precision. Both the frameworks can acquire exactness in the scope of 98% to 99.5% contingent on the quantity of classes being assessed.

CNN can be joined with various structures to further develop include extraction quality, and in this manner further develop grouping execution. Work in [16] proposes a CNN model that involves Walsh capacities to actually arrange information which depends on changing over 1D ECG signals into 2D picture like information. This is finished by planning different estimated Walsh lattices, and afterward involving them for include planning in the completely associated brain network layers to recognize least distance classes. Where, d_c is the base class contrast, 'Accomplishment' is the component vector, 'W' is the Walsh network coefficients, and 'j' is the level of Walsh work being utilized for examination. Because of the utilization of this base class distinction work, a precision of almost 100% is acquired on the MIT-BIH dataset. Walsh capacities can be supplanted with other exceptionally complex descriptors to work on this exactness. Abdullah et al.[17] highlights are then given to a help vector machine (SVM) classifier to get a precision of 99.9% on 10000 examples from the MIT-BIH dataset. The framework utilizes this multitude of element vectors and SVM classifiers separately, and afterward joins them involving 'mode' activity to acquire most often happening classes for conclusive grouping. SVM can be supplanted with CNN to get a comparable exactness of 99.7% as seen from [18], wherein atrial fibrillation and ordinary sinus musicality are grouped from the standard MIT-BIH dataset.

Journal of Theoretical and Applied Information Technology
28th February 2025. Vol.103. No.4
© Little Lion Scientific
ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Hence, it ensembling of profound learning models with direct classifiers results into an exceptionally exact ECG arrangement framework. In the following area, plan of such an outfit based model that joins CNN with kNN, irregular backwoods (RF) and SVM based classifier is examined. This is trailed by factual assessment of the proposed model, and its correlation with the absolute most proficient CNN-based models. At long last, this text closes for certain perceptions and future exploration headings which can be taken up by scientists to additionally further develop execution of proposed model, and extend it the equivalent to various kinds of datasets.

3. PROPOSED HIGH-PERFORMANCE ECG CLASSIFICATION MODEL USING HYBRID GENETIC MACHINE LEARNING MODEL (GM2LH)

In this research work, to enhance the precision values an outfit CNN framework added with classifier is proposed.The used classifier is a biomotivated and straight classifier. This plan consolidates VGGNet motivated CNN plan, bio-propelled irregular woodland model, direct help vector machine (SVM) and kNN classifier together to lessen grouping blunders. The proposed model is shown in figure 2.

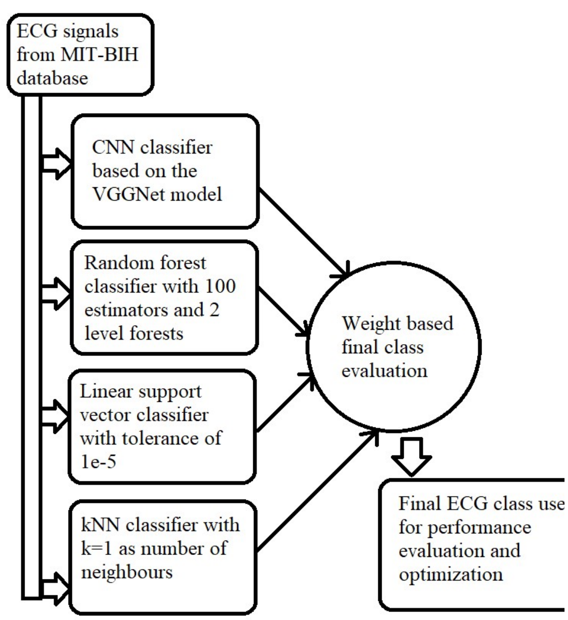

Figure 2. Block Diagram For The Ensemble Classification Model

The proposed model peruses the whole MIT-BIH dataset, and gives it to every one of the arrangement motors. Engineering of the VGGNet based CNN motor can be seen from the accompanying table 1, wherein various layers, and their utilization portrayal is given. It can likewise be seen that every one of the layers, and their arrangements assume a significant part in order by performing powerful component extraction and determination procedure on the crude natural ECG dataset.

Table 1. Architecture Of Proposed CNN Model And Its Layer-Wise Purpose

Layer No.	Design	Purpose
1	1D Convolutional layer (16x1 size), (5x1 kernel size) and ReLU activation	This layer is utilized to separate 16 highlights for every step of the ECG waveform. The step is moved through a 5x1 window for viable component extraction.
2	1D Convolutional layer(16x1 size), (5x1 kernel size) and ReLU activation	This layer is utilized to separate 16 highlights for each step of the ECG waveform. The step is moved through a 5x1 window for successful element extraction..
3	Pool size of 2x1(Maximum)	Most extreme worth of component change is separated from the extricated elements, and highlights are decreased by an element of 2. And that implies that the quantity of highlights is divided in this interaction.

4	Rate of drop out layer = 0.1	Roughly 10% of elements are eliminated for advancement of component determination process.
5	1D Convolutional layer (32x1 size) , (3x1 kernel size) and ReLU activation	This layer is utilized to separate 32 highlights for every step of the ECG waveform. The step is moved through a 3x1 window for viable component extraction.
6	1D Convolutional layer(32x1 size) , (3x1 kernel size) and ReLU activation	This layer is utilized to separate 32 highlights for each step of the ECG waveform. The step is moved through a 3x1 window for successful element extraction.
7	Pool size of 2x1(Maximum)	Most extreme worth of component change is separated from the extricated elements, and highlights are decreased by an element of 2. And that implies that the quantity of highlights is split in this cycle.
8	Rate of Drop out layer= 0.1	Around 10% of elements are taken out for streamlining of component determination process.
9	1D Convolutional layer (32x1 size) , (3x1 kernel size) and ReLU activation	This layer is utilized to separate 32 highlights for every step of the ECG waveform. The step is moved through a 3x1 window for viable component extraction.
10	1D Convolutional layer(32x1 size) , (3x1 kernel size) and ReLU activation	This layer is utilized to separate 32 highlights for each step of the ECG waveform. The step is moved through a 3x1 window for successful element extraction.
11	Pool size of 2x1(Maximum)	Most extreme worth of component change is separated from the extricated elements, and highlights are decreased by an element of 2. And that implies that the quantity of highlights is split in this cycle.
12	Rate of drop out layer= 0.1	Around 10% of elements are taken out for streamlining of component determination process.
13	1D Convolutional layer(256 size) , (3x1 kernel size) and ReLU activation	This layer is utilized to separate 256 highlights for every step of the ECG waveform. The step is moved through a 3x1 window for viable

		component extraction.
14	1D Convolutional layer (256 size) , (3x1 kernel size) and ReLU activation	This layer is utilized to separate 256 highlights for each step of the ECG waveform. The step is moved through a 3x1 window for successful element extraction.
15	Pool size of 2x1(Maximum)	Most extreme worth of component change is separated from the extricated elements, and highlights are decreased by an element of 2. And that implies that the quantity of highlights is divided in this interaction.
16	Rate of drop out layer= 0.2	Roughly 20% of elements are eliminated for advancement of component determination process.
17	Dense layer with 64x1 size and ReLU activation	Include decrease through thick layers, to such an extent that in each step 64 elements are joined to frame a solitary component esteem.
18	Dense layer with 64x1 size and ReLU activation	Include decrease through thick layers, with the end goal that in each step 64 elements are joined to frame a solitary component esteem.
19	Dense layer with Nx1 size and Softmax activation	This is a completely associated layer for definite arrangement into 1 of 'N' classes.

The scanty clear-cut cross-entropy (SCCE) is used to frame the CNN. This is prepared to enhance the precision level. This cannot separate between some CVD classes through highlight convolutions. Subsequently, the equivalent dataset is inputted to a discrete wavelet change motor. This is useful to access wavelet highlights. The KNN, SVM and RF classifiers are made by using these elements. Then, each data set is inputted to each of the classifiers and the accompanying condition is utilized to track down the last class.

$$C_{out} = w_{cnn} * C_{cnn} + w_{knn} * C_{knn} + w_{svm} * C_{svm} + w_{rf} * C_{rf} \dots (1)$$

Where, 'w' are the weight elements, and 'C' are the classifier classes. The Weight factors seen that the accompanying upsides of weight are generally ideal for the proposed model,

$$w_{cnn} = 0.6, w_{knn} = 0.2,$$

$$w_{svm} = 0.1 \ and \ w_{rf} = 0.1$$

In this way, the last class for the given ECG waveform is assessed and put away for additional exhibition correlation. To assess execution of the proposed model, the following segment utilizes whole dataset, and separates it into two halves for assessment of exactness, accuracy, review and f-Measure values. These qualities are contrasted and a portion of the cutting-edge techniques as considered from the writing.

4. RESULTS AND COMPARATIVE ANALYSIS

Assessment of execution for the proposed model requires an enormous assortment of ECG datasets to be utilized for preparing and testing purposes. To assemble this information the MIT-BIH dataset is utilized. A sum of 132k records were gathered for this reason, and every one of these records are sorted into 5 distinct CVD classes. Exactness,

Journal of Theoretical and Applied Information Technology
28th February 2025. Vol.103. No.4

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

accuracy, review and fMeasure values were looked at for CVD grouping for the proposed model and the models characterized in [4], [15] and [18]. The accompanying table 1 demonstrates the precision execution of the proposed model w.r.t. number of ECG passages utilized for testing. The dataset was separated into 70:30, wherein 77k records were utilized for preparing the model, while staying 55k records were utilized for testing the model and assessing its exhibition. The accompanying table 2 features the test exactness (TA) execution of the relative multitude of models.

Table 2. Test accuracy for combined dataset

No. of ECGs	**TA (%) [4]**	**TA (%) [15]**	**TA (%) [18]**	**TA (%) Proposed**
2k	97.06	97.35	97.26	98.21
4k	97.21	97.50	97.41	98.36
6k	97.36	97.65	97.56	98.51
8k	97.41	97.70	97.61	98.56
10k	97.46	97.75	97.66	98.61
15k	97.56	97.85	97.76	98.71
20k	97.61	97.90	97.81	98.77
22k	97.66	97.95	97.86	98.82
24k	97.76	98.05	97.96	98.92
28k	97.81	98.10	98.01	98.97
30k	97.86	98.15	98.06	99.01
35k	97.96	98.26	98.16	99.11
40k	98.06	98.36	98.26	99.21
45k	98.21	98.51	98.41	99.36
50k	98.46	98.76	98.66	99.47
55k	98.61	98.91	98.81	99.78

From the test exactness, it very well may be seen that the proposed model is exceptionally productive, and as better execution when contrasted with cutting edge characterization models. Normal exactness is around 2% higher when contrasted with these models, and can be seen from the accompanying figure 3, wherein these precision values are plotted.

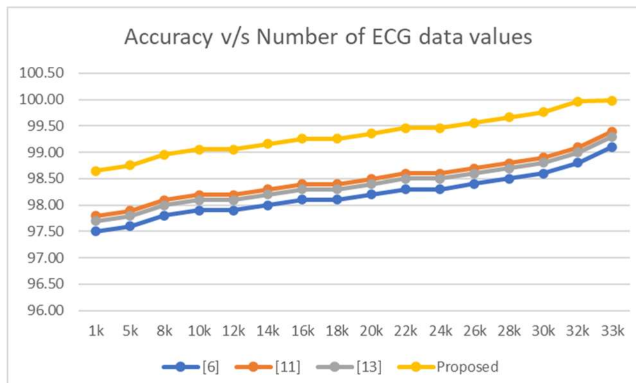

Figure 3. Average Accuracy For Different Algorithms

The following table 3and figure 4 showcases the test precision (TP) performance of all the models.

Table 3. Test Precision For Combined Dataset

No. of ECGs	**TP (%) [4]**	**TP (%) [15]**	**TP (%) [18]**	**TP (%) Proposed**
2k	92.21	96.38	93.36	97.72
4k	92.35	96.53	93.51	97.87
6k	92.50	96.68	93.65	98.02
8k	92.55	96.73	93.70	98.07

10k	92.59	96.78	93.75	98.12
15k	92.69	96.88	93.84	98.22
20k	92.74	96.93	93.89	98.27
22k	92.78	96.98	93.94	98.32
24k	92.88	97.07	94.03	98.42
28k	92.93	97.12	94.08	98.47
30k	92.97	97.17	94.13	98.52
35k	93.06	97.27	94.22	98.62
40k	93.16	97.37	94.32	98.72
45k	93.30	97.52	94.46	98.87
50k	93.54	97.77	94.70	98.98
55k	96.14	98.41	96.83	99.43

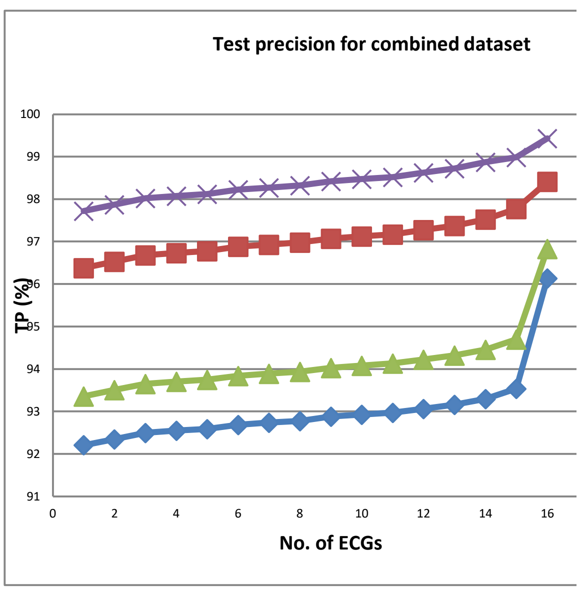

Figure 4. Test Precision For Combined Dataset

From the test accuracy values, it tends to be seen that the proposed model is exceptionally productive, and as better execution when contrasted with cutting edge order models. Normal accuracy is around 4% higher when contrasted with these models. The accompanying table 4& figure 5 exhibits the test review (TR) execution of the multitude of models.

Table 4. Test Recall For Combined Dataset

No. of ECGs	**TR (%) [4]**	**TR (%) [15]**	**TR (%) [18]**	**TR (%) Proposed**
2k	94.64	96.87	95.31	97.96
4k	94.79	97.01	95.46	98.11
6k	94.93	97.16	95.60	98.27
8k	94.98	97.21	95.65	98.32
10k	95.02	97.26	95.70	98.37
15k	95.12	97.36	95.80	98.47
20k	95.17	97.41	95.85	98.52
22k	95.22	97.46	95.90	98.57
24k	95.32	97.56	96.00	98.67
28k	95.36	97.61	96.04	98.72
30k	95.41	97.66	96.09	98.77
35k	95.51	97.76	96.19	98.87
40k	95.61	97.86	96.29	98.97
45k	95.76	98.01	96.44	99.11
50k	96.00	98.26	96.68	99.22

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

55k	97.37	98.66	97.82	99.36

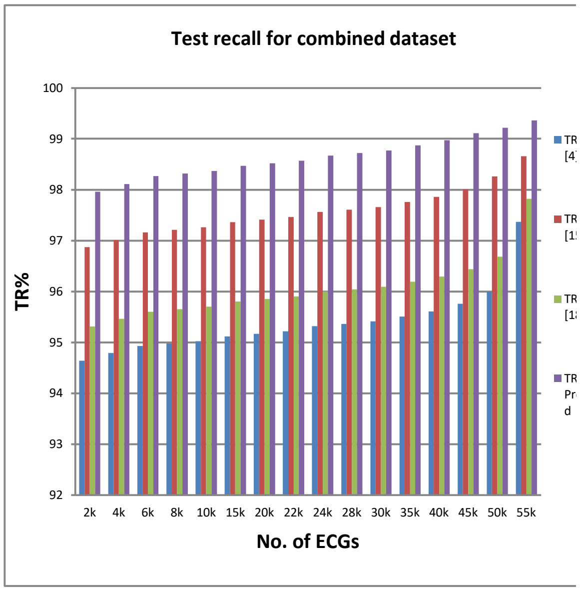

Figure 5 Test Recall For Combined Dataset

From the test review, it tends to be seen that the proposed model is profoundly proficient, and as better execution when contrasted with cutting edge grouping models. Normal review is around 3% higher when contrasted with these models. The accompanying table 5 and figure 6 stands the test fMeasure (TF) execution of the relative multitude of models.

Table 5. Test Fmeasure For Combined Dataset

No. of ECGs	TF (%) [4]	TF (%) [15]	TF (%) [18]	TF (%) Proposed
2k	93.41	96.63	94.33	97.84
4k	93.55	96.78	94.47	97.99
6k	93.70	96.93	94.62	98.14
8k	93.74	96.98	94.67	98.19
10k	93.79	97.02	94.72	98.24
15k	93.89	97.12	94.81	98.34
20k	93.94	97.17	94.86	98.39
22k	93.99	97.22	94.91	98.44
24k	94.08	97.32	95.00	98.54
28k	94.13	97.36	95.05	98.60
30k	94.17	97.41	95.10	98.65
35k	94.27	97.51	95.19	98.75
40k	94.37	97.61	95.29	98.85
45k	94.51	97.76	95.44	99.00
50k	94.75	98.01	95.68	99.10
55k	96.75	98.53	97.32	99.39

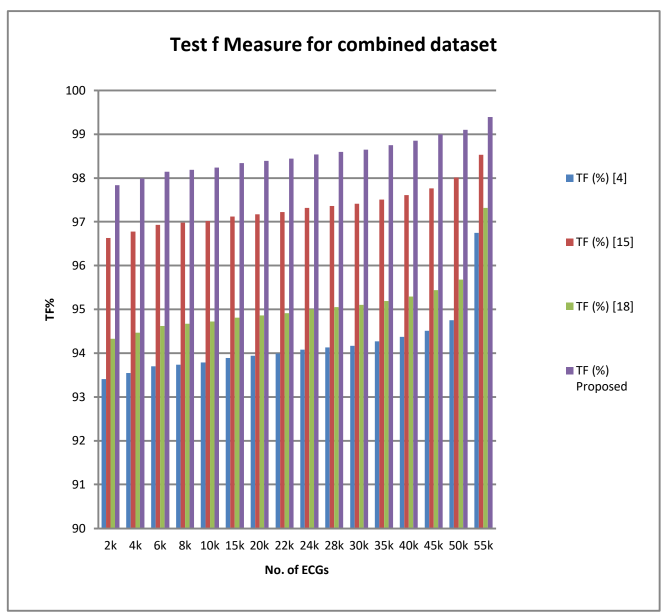

Figure 6 Test Fmeasure For Combined Dataset

From the test fMeasure, it very well may be seen that the proposed model is exceptionally productive, and as better execution when contrasted with cutting edge grouping models. Normal fMeasure is around 3% higher when contrasted with these models. It very well may be seen that the proposed calculation is predominant as far as all the presentation boundaries when contrasted on various datasets and various calculations. The exactness of this model is immersed, and consequently must be improved imperceptibly by utilizing prevalent profound learning models for the equivalent datasets.

The proposed hybrid Genetic Machine Learning Model (GM2LH) has demonstrated superior performance in ECG classification, achieving high accuracy, precision, recall, and f-measure values. By integrating CNN with classifiers such as Random Forest, SVM, and kNN, along with the application of wavelet transformation for feature extraction, the model effectively minimizes classification errors. Comparative analysis against state-of-the-art models confirms that the proposed method outperforms existing approaches with a notable accuracy of 99.98%. These findings highlight the model's potential for real-time applications in cardiovascular disease detection.

5. CONCLUSION AND FUTURE SCOPE

Because of the gathering of CNN with arbitrary woodland, SVM and kNN characterization models, by and large execution of the proposed model is exceptionally high. One more justification behind this superior execution is the utilization of wavelet change for include extraction, which attempts to lessen full length by amplifying fluctuation between highlight sets of various classes. Because of which the framework has an exactness of 99.98%, which is right now most noteworthy among all the cutting edge calculations and this is the strength of the work. The framework additionally delivers high accuracy of 99.48%, high review of 99.73%, which creates a high fMeasure worth of 99.6%. This large number of values are at present most noteworthy when contrasted and the as of late proposed calculations. Execution of this model is tried on MIT-BIH standard dataset, which makes the framework appropriate for ongoing use cases. It is prompted that the framework should be tried for other ECG datasets, including however not restricted to Physionet, PTB Datasets, Mendeley datasets, and so on Besides, it is additionally suggested that specialists should assess ongoing energy utilization of this model, and attempt to upgrade it for clinical use cases. Future research should focus on testing the model with diverse ECG datasets and optimizing energy efficiency for clinical use.

REFERENCES

[1] Tyagi, A. en Mehra, R. (2021) “Intellectual heartbeats classification model for diagnosis of heart disease from ECG signal using hybrid convolutional neural network with GOA”, SN Applied Sciences. Springer Science and Business Media LLC, 3(2). doi: 10.1007/s42452-021-04185-4.
[2] Huang, J.-S. et al. (2020) “Accurate classification of ECG arrhythmia using MOWPT enhanced fast compression deep learning networks”, Journal of ambient intelligence and humanized computing. Springer Science and Business Media LLC. doi: 10.1007/s12652-020-02110-y.
[3] Ju, C. et al. (2020) “Federated transfer learning for EEG signal classification”, in 2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC). 2020 42nd Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) in conjunction with the 43rd Annual Conference of the Canadian Medical and Biological Engineering Society, IEEE. doi: 10.1109/embc44109.2020.9175344.
[4] Arumugam, M. en Sangaiah, A. K. (2020) “Arrhythmia identification and classification using wavelet centered methodology in ECG signals”, Concurrency and computation: practice & experience. Wiley, 32(17). doi: 10.1002/cpe.5553.
[5] Zhang, Yuwei et al. (2020) “Wearable ECG signal processing for automated cardiac arrhythmia classification using CFASE-based feature selection”, Expert systems. Wiley, 37(1), bl e12432. doi: 10.1111/exsy.12432.
[6] Neela, T. en Namburu, S. (2021) “ECG signal classification using capsule neural networks”, IET networks. Institution of Engineering and Technology (IET), 10(3), bll 103–109. doi: 10.1049/ntw2.12018.
[7] Fradi, M. et al. (2021) “Automatic heart disease class detection using convolutional neural network architecture-based various optimizers-networks”, IET Smart Cities. Institution of Engineering and Technology

(IET), 3(1), bll 3–15. doi: 10.1049/smc2.12003.

[8] Kumar, P. en Sharma, V. K. (2020) “Detection and classification of ECG noises using decomposition on mixed codebook for quality analysis”, Healthcare technology letters. Institution of Engineering and Technology (IET), 7(1), bll 18–24. doi: 10.1049/htl.2019.0096.

[9] Bouaziz, F. et al. (2019) “Automatic ECG arrhythmias classification scheme based on the conjoint use of the multi-layer perceptron neural network and a new improved metaheuristic approach”, IET signal processing. Institution of Engineering and Technology (IET), 13(8), bll 726–735. doi: 10.1049/iet-spr.2018.5465.

[10] Xu, Y. et al. (2021) “Extreme learning machine for heartbeat classification with hybrid time-domain and wavelet time-frequency features”, Journal of healthcare engineering, 2021, bl 6674695. doi: 10.1155/2021/6674695.

[11] Yang, H. en Wei, Z. (2020) “Arrhythmia recognition and classification using combined parametric and visual pattern features of ECG morphology”, IEEE access: practical innovations, open solutions. Institute of Electrical and Electronics Engineers (IEEE), 8, bll 47103–47117. doi: 10.1109/access.2020.2979256.

[12] Kiranyaz, S., Ince, T. en Gabbouj, M. (2016) “Real-time patient-specific ECG classification by 1-D convolutional neural networks”, IEEE transactions on bio-medical engineering. Institute of Electrical and Electronics Engineers (IEEE), 63(3), bll 664–675. doi: 10.1109/tbme.2015.2468589.

[13] Amirshahi, A. en Hashemi, M. (2019) “ECG classification algorithm based on STDP and R-STDP neural networks for real-time monitoring on ultra low-power personal wearable devices”, IEEE transactions on biomedical circuits and systems. Institute of Electrical and Electronics Engineers (IEEE), 13(6), bll 1483–1493. doi: 10.1109/tbcas.2019.2948920.

[14] Abdalla, F. Y. O. et al. (2020) “Deep convolutional neural network application to classify the ECG arrhythmia”, Signal, image and video processing. Springer Science and Business Media LLC, 14(7), bll 1431–1439. doi: 10.1007/s11760-020-01688-2.

[15] Song, X. et al. (2020) “Short term ECG classification with residual-concatenate network and metric learning”, Multimedia tools and applications. Springer Science and Business Media LLC, 79(31–32), bll 22325–22336. doi: 10.1007/s11042-020-09035-w.

[16] Dokur, Z. en Ölmez, T. (2020) “Heartbeat classification by using a convolutional neural network trained with Walsh functions”, Neural computing & applications. Springer Science and Business Media LLC, 32(16), bll 12515–12534. doi: 10.1007/s00521-020-04709-w.

[17] Abdullah, D. A., Akpınar, M. H. en Şengür, A. (2020) “Local feature descriptors based ECG beat classification”, Health information science and systems. Springer Science and Business Media LLC, 8(1), bl 20. doi: 10.1007/s13755-020-00110-y.

[18] Huang, M.-L. en Wu, Y.-S. (2020) “Classification of atrial fibrillation and normal sinus rhythm based on convolutional neural network”, Biomedical engineering letters. Springer Science and Business Media LLC, 10(2), bll 183–193. doi: 10.1007/s13534-020-00146-9.