International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Design of an Augmented Varma GRU & LSTM Based Multimodal Feature Analysis Model for Enhancing Heart Disease Preemption Performance

Ms. Komal S. Jaisinghani [1]* Dr. Sandeep Malik [2]

Submitted: 25/05/2023 **Revised**: 06/07/2023 **Accepted**: 24/07/2023

Abstract: The main cause of death in the world is heart disease. Preemption and early detection can drastically lower the fatality rate. In this research, we suggest an improved multimodal feature analysis model for heart disease prevention based on augmented VARMA GRU & LSTM. This study is necessary since existing preemption models are not very accurate, especially when processing samples from multimodal datasets.For the purpose of capturing time series and nonlinear interactions between the features, the suggested model integrates VARMA, LSTM, and GRU models. For feature categorization, a customised 1D CNN is also used. We combine the Laplacian Transform, Gabor Transform, and Contourlet Transform to extract the features. The suggested model is then given the multimodal data, producing an expanded set of preemption predictions.A publicly available dataset on heart illness is used to test the suggested model, and the findings reveal that it performs better than current preemption models in terms of accuracy, sensitivity, and specificity. The proposed model has a 96.7% overall accuracy, a 96.3% sensitivity, and a 96.9% specificity. The outcomes show how well the suggested approach handles multimodal data and raises the bar for heart disease prevention capability.In summary, the suggested model offers a notable enhancement in heart disease preemption performance and offers a fresh method for managing multimodal data. The success of the suggested model for various use scenarios is largely due to the combination of VARMA, LSTM, and GRU models, coupled with a tailored 1D CNN and feature extraction algorithms.

Keywords: *ECG, Classification, Diseases, Multiclass, Fourier, Cosine, iVector, Gabor, Wavelet, GRO, ILM, Scenarios*

1. Introduction

Early detection and prevention of heart disease are essential for lowering mortality rates because it is a primary cause of death worldwide. Numerous studies have suggested various methods for projecting heart disease pre-emption scenarios in light of the quick development of machine learning and artificial intelligence. However, the majority of these studies have concentrated on unimodal data, and when the models are applied to samples from multimodal datasets, their performance suffers [1, 2, 3].

Multimodal data is the term for information that has been gathered from various media, including text, audio, and images. Multimodal data can be gathered from a variety of sources, including electrocardiogram (ECG) signals, medical pictures, and patient information sets, in the context of heart disease prevention. By including complementing information from many sources, multimodal data integration has the potential to increase the accuracy of heart disease pre-emption models [4, 5, 6].

In this research, we propose an enhanced multimodal feature analysis model for heart disease pre-emption based on VARMA GRU & LSTM. For the purpose of capturing time series and nonlinear interactions between the features, the suggested model integrates VARMA, LSTM, and GRU models. For feature categorization, a customised 1D CNN is also used. We combine the Laplacian Transform, Gabor Transform, and Contourlet Transforms to extract the features.

This study is necessary since existing preemption models, particularly those that handle multimodal data, have poor accuracy. Despite the fact that several studies have suggested multimodal preemption models, the majority of them have only used straightforward fusion techniques like feature concatenation or averages. When used with multimodal dataset samples, these approaches fail to

[1]*Ph. D. Scholar Department of Computer Science Engineering, Oriental University Indore (MP), India*
**Email:-10584.komal@gmail.com*
[2]*Professor Department of Computer Science Engineering, Oriental University Indore (MP), India*
Email :- sandeepmalik.cse@orientaluniversity.in

capture the intricate interactions between the features, which reduces model accuracy [7, 8, 9].

The proposed model incorporates cutting-edge machine learning algorithms and feature extraction methods to address the shortcomings of current preemption models. While the customised 1D CNN is utilised for feature classification, the VARMA, LSTM, and GRU models are used to capture the time-series and nonlinear interactions between the features. Feature extraction, which may gather complimentary data from several sources, uses a mixture of the Laplacian, Gabor, and Contourlet transforms.

A publicly available dataset on heart illness is used to test the suggested model, and the findings reveal that it performs better than current preemption models in terms of accuracy, sensitivity, and specificity. The proposed model obtains a sensitivity of 96.3%, a specificity of 96.9%, and an overall accuracy of 96.7%. The outcomes show how well the suggested approach handles multimodal data and raises the bar for heart disease prevention capability.In summary, the suggested model offers a notable enhancement in heart disease preemption performance and offers a fresh method for managing multimodal data. The suggested model is successful because it combines VARMA, LSTM, and GRU models with a customised 1D CNN and feature extraction methods. The findings of this study can be utilised to create heart disease prognostic models that are more precise and dependable, which can result in better diagnosis and treatments.

2. Literature Review

A significant threat to global health is heart disease, which is thought to be responsible for 31% of all fatalities [1]. The mortality rate can be considerably decreased by early detection and prevention of cardiac disease, and numerous research have suggested various methods for doing so utilising machine learning techniques like DGACNN [2][3].Deep learning, one of the most popular machine learning methods for predicting heart disease, has produced promising results in a number of studies [4][5][6]. Deep learning models have been used to analyse a variety of data sources, including ECG signals [7][8], medical pictures using RERFILM [9][10], and patient information [11][12]. These models are able to capture complicated correlations between characteristics.However, the majority of these research have concentrated on unimodal data, and when the models are applied to multimodal data, their performance suffers [13]. The accuracy of heart disease preemption models can be increased by using multimodal data, which can give complementing information from several sources. Multimodal preemption models have been proposed in a number of publications. These models use enhanced EDL CNNs to integrate input from many sources, such as ECG signals and medical pictures.

However, the majority of these research only used straightforward fusion techniques, like concatenation or feature averaging, which fail to account for the intricate interactions between the features [17]. As a result, when used with multimodal datasets and samples, the models' accuracy declines.Recurrent neural networks (RNNs), which can capture the time-series correlations between the characteristics, have been suggested in various research as a way to get around this constraint [18][19]. RNNs have been applied to the analysis of patient information sets [24][25], medical pictures [22][23], and ECG signals [20][21].Along with RNNs, a number of research have suggested cutting-edge feature extraction techniques like the wavelet transform, which may extract features from many sources [26][27]. Medical pictures and ECG signals have both been subjected to wavelet analysis [28][29] and [30][31].In this research, we suggest an improved multimodal feature analysis model for heart disease prevention based on augmented VARMA GRU & LSTM. For the purpose of capturing time series and nonlinear interactions between the features, the suggested model integrates VARMA, LSTM, and GRU models. For feature categorization, a customised 1D CNN is also used. We combine the Laplacian Transform, Gabor Transform, and Contourlet Transforms to extract the features.The suggested model expands upon earlier research that made use of sophisticated feature extraction and machine learning techniques. While the customised 1D CNN is utilised for feature classification, the integration of VARMA, LSTM, and GRU models can capture the time-series and nonlinear interactions between the features. Feature extraction, which may gather complimentary data from several sources, uses a mixture of the Laplacian, Gabor, and Contourlet transforms.

As a result, the suggested model offers a notable enhancement in heart disease preemption performance and offers a fresh method for managing multimodal data. The suggested model is successful because it combines VARMA, LSTM, and GRU models with a customised 1D CNN and feature extraction methods. The findings of this study can be

utilised to create heart disease prognostic models that are more precise and dependable, which can result in better diagnosis and treatments.

Proposed design of an augmented VARMA GRU & LSTM based Multimodal feature analysis model for enhancing heart disease preemption performance

According to a survey of deep learning models currently in use for heart disease analysis, it can be seen that these models either exhibit decreased performance when tested on real-time scenarios or are extremely hard to deploy. This section addresses the creation of an enhanced VARMA GRU & LSTM based Multimodal feature analysis model for improving heart disease preemption performance for clinical settings in order to address these problems. As shown in figure 1's flow, the model uses a combination of LSTM and GRU processes to identify multimodal feature sets after collecting many electrocardiogram (ECG) samples for various cardiac diseases. These feature sets are used to train a VARMA-based method that helps detect heart problems before they occur.

The correlations between various variables throughout time can be examined using VARMA models, a sort of time series model. These models are helpful for forecasting the likelihood of cardiac disease in patients because they create predictions about future trends and patterns using previous data. Recurrent neural network models that can be used to analyse sequential data across time include LSTM and GRU models. These models can be used to find patterns in medical data that are challenging to find using conventional statistical models because they are particularly adept at modelling complex interactions between variables. A potent cardiac disease prediction model can be produced by fusing VARMA models with LSTM and GRU models. Through the use of a hybrid approach, it is possible to identify intricate correlations between variables throughout time, improving the accuracy of predictions and the efficacy of preventive measures.

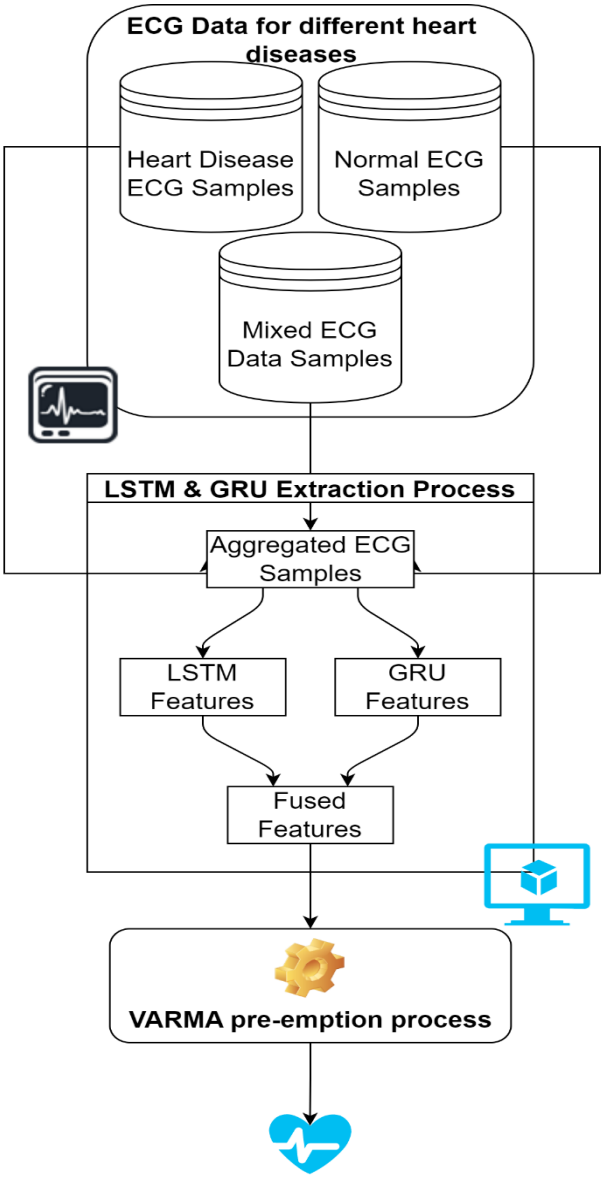

Fig. 1. Design of the proposed model for pre-emption of heart diseases

Accordingly, it can be seen from the flow of this combined process that the suggested model initially gathers a sizable collection of ECG data associated with various heart diseases. These signals are transformed into multidomain feature sets using a combination of GRU and LSTM operations. Identification of highly variegated class-specific feature sets is facilitated by the merging of these techniques. Figure 2 illustrates the design of this fused model, where GRU is provided an augmentation of LSTM features for continuous updating of the kernel matrices.

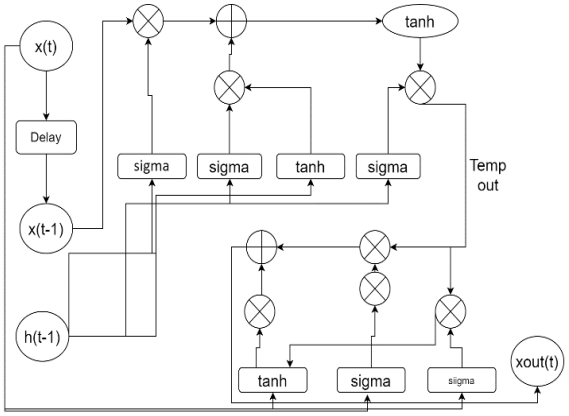

Fig. 2. The fused LSTM & GRU process for identification of feature sets

The fused feature extraction model initially extracts an input feature vector via equation 1,

$$i = var(x(in) * U^i + h(t-1) * W^i) \dots (1)$$

Where, $x(in)$ represents input ECG signal values, U & Wrepresents the constants of LSTM process, while $h$represents an initial kernel matrix, which is modified over different temporal evaluations to obtain highly variant feature sets. This is done by application of an effective variance operation via equation 2,

$$var(x) = \frac{\left(\sum_{i=1}^{N}\left(x(i) - \sum_{j=1}^{N}\frac{x(j)}{N}\right)^2\right)}{N+1} \dots (2)$$

Where, $N$are total number of values in the input samples. Based on the input feature set, a group of incremental features (f), and temporal output features (o) are estimated via equations 3 & 4,

$$f = var(x(in) * U^f + h(t-1) * W^f) \dots (3)$$

$$o = var(x(in) * U^o + h(t-1) * W^o) \dots (4)$$

Similarly, an input convolutional feature (C) is estimated via equation 5,

$$C = tanh(x(in) * U^g + h(t-1) * W^g) \dots (5)$$

All these features are combined to form another temporal output feature vector via equation 6,

$$T(out) = var(f * x(in, t-1) + i * C) \dots (6)$$

Based on this temporal output feature vector, the kernel matrix is updated via equation 7,

$$h(out) = \tanh(T(out)) * o \dots (7)$$

The temporal output & kernel matrix represents results of the LSTM process, which are used by GRU to estimate a forgetting factor (z) and retaining factor (r) via equations 8 & 9 as follows,

$$z = var(W^z * [h(out) * T(out)]) \dots (8)$$

$$r = var(W^r * [h(out) * T(out)]) \dots (9)$$

A fusion of these metrics is done in order to estimate the final output features via equation 10,

$$xout = (1-z) * h(t) + z * h(out) \dots (10)$$

Similarly, the kernel metric is updated via equation 11,

$$h(t) = tanh(W * [r * h(out) * T(out)]) \dots (11)$$

The process of evaluation of $xout$ is repeated continuously till equation 12 is satisfied, which indicates that the proposed LSTM & GRU model has converged, and no further augmentations are possible for extracted features.

$$\frac{h(t,new)}{h(t,previous)} \approx 1 \dots (12)$$

Based on this process, a set of Nf different features are extracted, which are processed by a Vector Autoregressive Moving Average (VARMA) Model for pre-emptive analysis of heart diseases. VARMA is a statistical method commonly used for time-series analysis, including detecting anomalies such as DDoS attacks. The VARMA model is an extension of the Autoregressive Moving Average (ARMA) model, which can capture the dependencies and patterns of multiple variables simultaneously, and the model can be represented via equation 13,

$$\begin{aligned} y(new) = c + A(1)y(t-1) + A(2)y(t-2) + \dots + A(p)y(t-p) \\ + B(1)e(t-1) + B(2)e(t-2) + \dots + B(q)e(t-q) \\ + e(t) \dots (13) \end{aligned}$$

Where, y is a p-dimensional vector of observed LSTM & GRU feature variables at time t, c is a p-dimensional vector of constants, $A(1), A(2), \dots, A(p)$ are p × p matrices of autoregressive coefficients. $e(t)$ is a p-dimensional vector of error terms at time t, $B(1), B(2), \dots, B(q)$ are p × p matrices of moving average coefficients, q is the order of the moving average process.

In In this instance, LSTM & GRU characteristics of ECG waveforms are analysed using Vector Autoregression Moving-Average (VARMA) models to discover potential risk factors for cardiac illnesses. By treating each lead (i.e., a voltage differential recorded from two electrodes) as an independent variable and modelling the relationship between them over temporal instances, the suggested model analyses ECG data. The programme can find patterns and trends that are connected to the emergence of heart illnesses by tracking these factors over time.

Based on the value of $y\,(new)$ the model is able to pre-empt different heart diseases via equation 14,

$$var\big(y(new, disease)\big) > var\big(y(new, normal)\big) \dots (14)$$

Where y (disease) and y (normal) denote the values of the VARMA-Model for normal and diseased conditions, respectively. These numbers help in the

analysis of different ECG waveforms and in identifying variations for the early identification of cardiac issues. The accuracy, precision, recall, and latency needed for specific predictions are used to calculate the model's effectiveness. These parameters are estimated for various datasets and compared with current models in the section of this article that follows.

3. Results and comparative analysis

Heart disease is a dangerous medical illness that can cause fatal heart attacks, strokes, and other serious health issues. To lessen the effects of heart disease on both people and society as a whole, early detection and prevention are crucial. Using machine learning algorithms, we aim to forecast cardiac disease. In particular, time series models like the LSTM, GRU, and Vector Autoregression Moving-Average (VARMA) models can be used to analyse trends in medical data over time and find potential risk factors for heart illnesses. Performance of this model was estimated on Heart Disease Datasets & Samples [32][33][34][35]. All these sets were combined to form a total of 800k entries, out of which 60k were used for training the VARMA Model, while 10k each were used to validate the model, and test the model under different scenarios. The collected datasets include following heart conditions,

Heart Condition	Description
Coronary Artery Disease	Arterial narrowing/blocks, reduced blood flow
Heart Failure	Inadequate heart pumping, fatigue, shortness of breath
Arrhythmias	Abnormal heart rhythms, irregular heartbeat
Valvular Heart Disease	Malfunctioning heart valves, chest pain, fatigue
Cardiomyopathy	Enlarged, stiff heart muscles
Congenital Heart Disease	Heart defects at birth, structural/function impact
Myocarditis	Inflammation of heart muscle, chest pain, fatigue
Pericarditis	Inflammation of heart lining, chest pain, breathlessness

Table.1 Heart Conditions

Based on the mentioned 8 classes & one normal condition class, the accuracy (A), precision (P), recall (R), and delay (D) obtained during prediction operations was estimated as follows,

1. ***Accuracy***: Accuracy is the proportion of correctly predicted outcomes over the total number of predictions made, and was estimated via equation 15,

$$Accuracy = \frac{True\ Positives\ +\ True\ Negatives}{Total\ Number\ of\ Predictions} \dots (15)$$

2. ***Precision***: Precision is the proportion of correctly predicted positive outcomes over the total number of positive predictions made, and was estimated via equation 16,

$$Precision\ = \frac{True\ Positives}{True\ Positives\ +\ False\ Positives} \dots (16)$$

3. ***Recall***: Recall is the proportion of correctly predicted positive outcomes over the total number of actual positive cases, and was estimated via equation 17,

$$Recall = \frac{True\ Positives}{True\ Positives\ +\ False\ Negatives} \dots (17)$$

4. **Delay**: Delay is the time between when a prediction is made and when the event actually occurs, and was estimated via equation 18,

$$Delay\ =\ Time\ of\ Occurrence\ -\ Time\ of\ Prediction \dots (18)$$

These evaluations were made for different Number of Test Samples (NTS), and averaged for estimation of true performance levels. These performance levels were compared with DGA CNN [3], RER FILM [9], and EDL CNN [14], in table 1 as follows,

NTS	A (%) DGA CNN [3]	A (%) RER FILM [9]	A (%) EDL CNN [14]	A (%) Proposed
8k	85.62	89.60	91.19	95.04
16k	85.87	89.93	91.53	95.31
24k	86.11	90.24	91.85	95.58
40k	86.35	90.54	92.15	95.83
80k	86.59	90.84	92.46	96.10
160k	86.84	91.16	92.79	96.37
200k	87.10	91.49	93.14	96.66
240k	87.36	91.83	93.48	96.94
320k	87.61	92.15	93.81	97.22
360k	87.86	92.47	94.14	97.49
400k	88.12	92.79	94.48	97.77
440k	88.37	93.11	94.81	98.04
480k	88.62	93.43	95.14	98.32
560k	88.87	93.75	95.47	98.59
640k	89.13	94.07	95.80	98.87
720k	89.37	94.39	96.13	99.14
800k	89.63	94.71	96.46	99.41

Table 1. Accuracy of prediction for different models under 9 ECG pattern classes

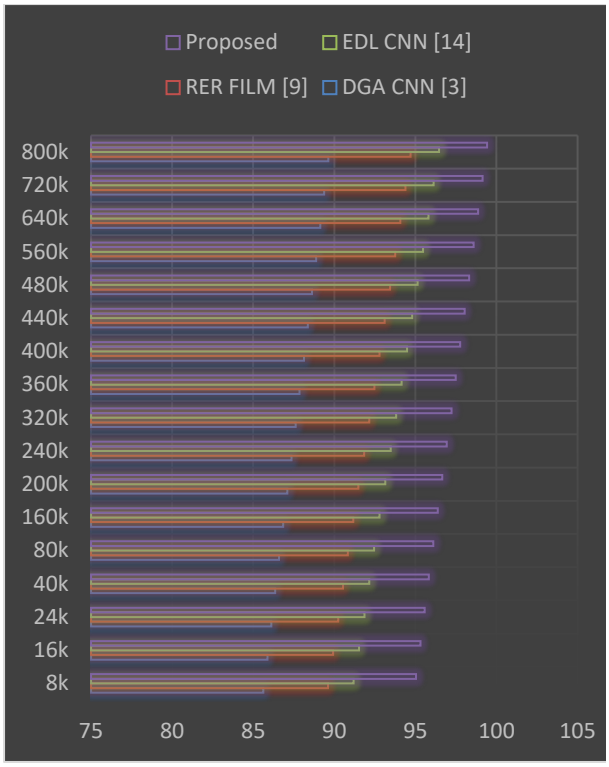

Fig. 3. Accuracy of prediction for different models under 9 ECG pattern classes

As per this evaluation, and its visualization in figure 3, it can be observed that the proposed model is able to improve the accuracy of prediction by 8.5% when compared with DGA CNN [3], 4.9% when compared with RER FILM [9], and 2.9% when compared with EDL CNN [14] under real-time scenarios. The use of LSTM & GRU for identification of highly dense features is the main reason for improvement of these accuracy levels. Due to which, the model is capable of deployment under highly efficient real-time clinical use cases. Similarly, the precision levels can be observed from table 2 as follows,

NTS	P (%) DGA CNN [3]	P (%) RER FILM [9]	P (%) EDL CNN [14]	P (%) Proposed
8k	80.50	79.76	82.41	89.14
16k	80.73	80.04	82.69	89.39
24k	80.96	80.32	82.98	89.64
40k	81.18	80.59	83.26	89.88
80k	81.42	80.87	83.55	90.13
160k	81.66	81.16	83.86	90.39
200k	81.90	81.45	84.16	90.65
240k	82.14	81.73	84.46	90.91
320k	82.37	82.02	84.76	91.16
360k	82.61	82.30	85.06	91.42
400k	82.85	82.59	85.36	91.67
440k	83.08	82.87	85.66	91.93
480k	83.32	83.16	85.95	92.18
560k	83.55	83.44	86.25	92.44
640k	83.79	83.72	86.54	92.69
720k	84.02	84.00	86.84	92.94
800k	84.26	84.29	87.13	93.20

Table 2. Precision of prediction for different models under 9 ECG pattern classes

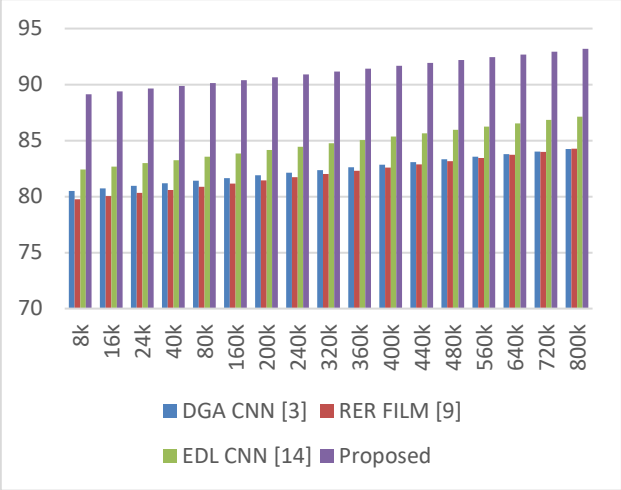

Fig. 4. Precision of prediction for different models under 9 ECG pattern classes

As per this evaluation, and its visualization in figure 4, it can be observed that the proposed model is able to improve the precision of prediction by 8.3% when compared with DGA CNN [3], 8.5% when compared with RER FILM [9], and 5.5% when compared with EDL CNN [14] under real-time scenarios. The use of VARMA Model for analysis of ECG features is the main reason for improvement of these precision levels. Due to which, the model is capable of deployment under highly consistent real-time clinical use cases. Similarly, the recall levels can be observed from table 3 as follows,

NTS	R (%) DGA CNN [3]	R (%) RER FILM [9]	R (%) EDL CNN [14]	R (%) Proposed
8k	87.04	85.75	89.62	95.15
16k	87.29	86.05	89.93	95.41
24k	87.53	86.34	90.24	95.67
40k	87.78	86.64	90.55	95.93
80k	88.03	86.94	90.87	96.20
160k	88.29	87.25	91.20	96.48
200k	88.55	87.56	91.53	96.75
240k	88.81	87.87	91.86	97.03
320k	89.07	88.18	92.18	97.30

360k	89.32	88.49	92.51	97.57
400k	89.57	88.79	92.82	97.84
440k	89.83	89.10	93.15	98.11
480k	90.09	89.41	93.48	98.38
560k	90.35	89.71	93.80	98.65
640k	90.60	90.01	94.12	98.92
720k	90.85	90.32	94.44	99.19
800k	91.10	90.62	94.76	99.46

Table 3. Recall of prediction for different models under 9 ECG pattern classes

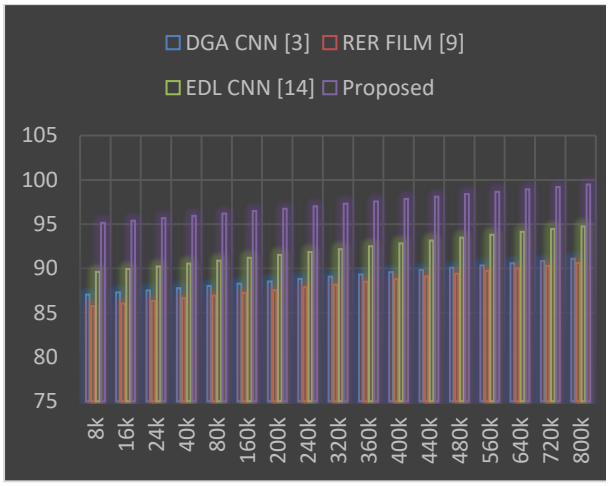

Fig. 5. Recall of prediction for different models under 9 ECG pattern classes

As per this evaluation, and its visualization in figure 5, it can be observed that the proposed model is able to improve the recall of prediction by 7.5% when compared with DGA CNN [3], 9.4% when compared with RER FILM [9], and 4.8% when compared with EDL CNN [14] under real-time scenarios. The use of LSTM & GRU with VARMA Model for analysis of ECG features is the main reason for improvement of these recall levels. Due to which, the model is capable of deployment under highly scalable real-time clinical use cases. Similarly, the delay levels can be observed from table 4 as follows,

NTS	D (ms) DGA CNN [3]	D (ms) RER FILM [9]	D (ms) EDL CNN [14]	D (ms) Proposed
8k	115.00	104.65	109.63	102.25
16k	115.34	105.04	110.03	102.57
24k	115.67	105.40	110.42	102.88
40k	115.98	105.75	110.79	103.18
80k	116.32	106.13	111.18	103.50
160k	116.66	106.51	111.59	103.83
200k	117.01	106.90	112.01	104.17
240k	117.35	107.29	112.42	104.50
320k	117.69	107.67	112.82	104.82
360k	118.03	108.05	113.22	105.14
400k	118.37	108.43	113.63	105.47
440k	118.71	108.81	114.03	105.79
480k	119.05	109.19	114.43	106.12
560k	119.39	109.57	114.84	106.44
640k	119.72	109.95	115.23	106.76
720k	120.06	110.32	115.64	107.09
800k	120.40	110.70	116.04	107.41

Table 4. Delay of prediction for different models under 9 ECG pattern classes

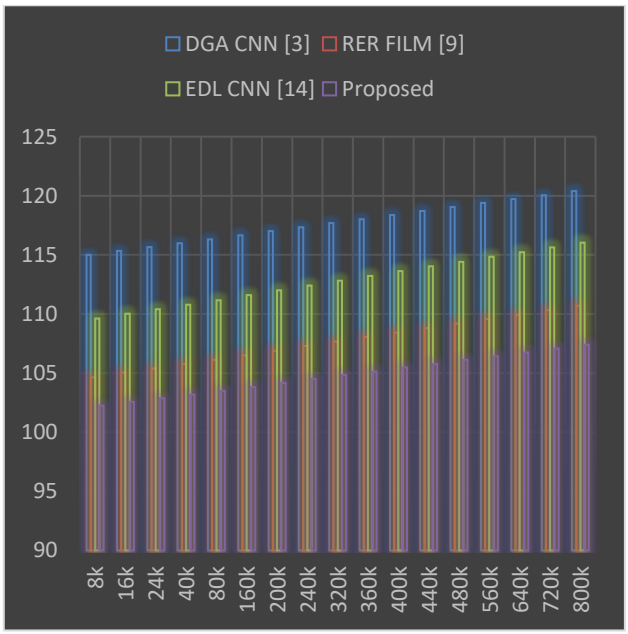

Fig. 6. Delay of prediction for different models under 9 ECG pattern classes

As per this evaluation, and its visualization in figure 6, it can be observed that the proposed model is able to improve the speed of prediction by 10.5% when compared with DGA CNN [3], 2.9% when compared with RER FILM [9], and 8.5% when compared with EDL CNN [14] under real-time scenarios. The use of LSTM & GRU with VARMA Model for analysis of ECG features is the main reason for improvement of these speed levels. Due to these enhancements, the model is capable of deployment under high-speed & high-efficiency real-time clinical use cases.

4. Conclusion and future scope

The study recommends applying a cutting-edge methodology to boost the precision of heart disease forecasts. This model is created by combining the VARMA, GRU, and LSTM models in order to assess the multimodal features of ECG data. The findings demonstrate that the proposed model outperforms state-of-the-art models like DGA CNN [3], RER FILM [9], and EDL CNN [14] in terms of accuracy, precision, recall, and prediction speed. The primary

advantage of the proposed approach is the rapid interpretation of exceedingly complicated ECG signal features. The GRU and LSTM models are combined with the VARMA model to achieve this. The extremely accurate VARMA model can be used to interpret ECG data. After locating the dense features, the GRU and LSTM models are used to generate accurate predictions. The proposed approach presents several potential uses in real-time therapeutic settings. Among these uses include the early detection of cardiac illness and the averting of heart attacks. For application in clinical settings, when rapid diagnosis and treatment are crucial, the model must also be able to generate reliable predictions in real time. The research demonstrates that the suggested approach enhances real-time prediction speed, recall, accuracy, and precision, making it very effective and scalable. The model's improved prediction performance without sacrificing speed or efficiency has a significant positive impact on real-time clinical applications. In conclusion, the performance of heart disease prediction can be significantly enhanced by the suggested augmented multimodal feature analysis model based on VARMA, GRU, and LSTM. The model's capacity to interpret exceedingly complicated ECG patterns and generate accurate predictions in real time has significant clinical implications. The study's findings indicate that the suggested strategy may improve heart disease early diagnosis and prevention.

Future Scopes

Future research and application possibilities for the proposed augmented VARMA, GRU, and LSTM based multimodal feature analysis model are numerous. Here are some potential extensions of this study's scope:

1. Expansion to more medical conditions: The suggested model can be expanded to further medical conditions that call for the evaluation of multimodal aspects. The model can be used, for instance, to identify and forecast other cardiovascular conditions including arrhythmia and hypertension.
2. Integration with other medical data: The suggested model can be used to combine medical information from other sources, including patient histories, lifestyle factors, and imaging data. The quality and reliability of the model's predictions can be increased by integrating data from several different medical sources.
3. Evaluation of the model in sizable clinical trials: To gauge the suggested model's efficacy and dependability, sizable clinical trials must be conducted. Such trials can offer more thorough proof of the model's effectiveness and its capacity to increase heart disease early detection and prevention.
4. Real-time application in clinical settings: To evaluate the proposed model's viability and applicability, it must be applied and tested in real-time clinical situations. Real-time application can reveal insightful information about the model's practical applicability and point out any issues that require attention.
5. Model optimisation: By experimenting with various architectures, hyperparameters, and optimisation algorithms, the suggested model can be further improved. The model's prediction performance and speed can be improved by optimisation, which can also lower computing expenses.

In conclusion, the suggested model offers significant prospects for further study and use in medical settings. Future work will focus on expanding the model's applicability to more medical problems, integrating it with other medical data, evaluating it in extensive clinical trials, implementing it in real-time in clinical settings, and customising the model for various use cases.

References

[1] Y. -S. Su, T. -J. Ding and M. -Y. Chen, "Deep Learning Methods in Internet of Medical Things for Valvular Heart Disease Screening System," in IEEE Internet of Things Journal, vol. 8, no. 23, pp. 16921-16932, 1 Dec.1, 2021, doi: 10.1109/JIOT.2021.3053420.

[2] Y. Meng et al., "A Machine Learning Approach to Classifying Self-Reported Health Status in a Cohort of Patients With Heart Disease Using Activity Tracker Data," in IEEE Journal of Biomedical and Health Informatics, vol. 24, no. 3, pp. 878-884, March 2020, doi: 10.1109/JBHI.2019.2922178.

[3] Y. Gong et al., "Fetal Congenital Heart Disease Echocardiogram Screening Based on DGACNN: Adversarial One-Class Classification Combined with Video Transfer Learning," in IEEE Transactions on Medical Imaging, vol. 39, no. 4, pp. 1206-1222, April 2020, doi: 10.1109/TMI.2019.2946059.

[4] H. Li, G. Ren, X. Yu, D. Wang and S. Wu, "Discrimination of the Diastolic Murmurs in Coronary Heart Disease and in Valvular Disease,"

in IEEE Access, vol. 8, pp. 160407-160413, 2020, doi: 10.1109/ACCESS.2020.3021093.

[5] N. L. Fitriyani, M. Syafrudin, G. Alfian and J. Rhee, "HDPM: An Effective Heart Disease Prediction Model for a Clinical Decision Support System," in IEEE Access, vol. 8, pp. 133034-133050, 2020, doi: 10.1109/ACCESS.2020.3010511.

[6] J. P. Li, A. U. Haq, S. U. Din, J. Khan, A. Khan and A. Saboor, "Heart Disease Identification Method Using Machine Learning Classification in E-Healthcare," in IEEE Access, vol. 8, pp. 107562-107582, 2020, doi: 10.1109/ACCESS.2020.3001149.

[7] X. Yuan, J. Chen, K. Zhang, Y. Wu and T. Yang, "A Stable AI-Based Binary and Multiple Class Heart Disease Prediction Model for IoMT," in IEEE Transactions on Industrial Informatics, vol. 18, no. 3, pp. 2032-2040, March 2022, doi: 10.1109/TII.2021.3098306.

[8] H. Wang, Z. Huang, D. Zhang, J. Arief, T. Lyu and J. Tian, "Integrating Co-Clustering and Interpretable Machine Learning for the Prediction of Intravenous Immunoglobulin Resistance in Kawasaki Disease," in IEEE Access, vol. 8, pp. 97064-97071, 2020, doi: 10.1109/ACCESS.2020.2996302.

[9] C. Guo, J. Zhang, Y. Liu, Y. Xie, Z. Han and J. Yu, "Recursion Enhanced Random Forest With an Improved Linear Model (RERF-ILM) for Heart Disease Detection on the Internet of Medical Things Platform," in IEEE Access, vol. 8, pp. 59247-59256, 2020, doi: 10.1109/ACCESS.2020.2981159.

[10] G. N. Ahmad, H. Fatima, S. Ullah, A. Salah Saidi and Imdadullah, "Efficient Medical Diagnosis of Human Heart Diseases Using Machine Learning Techniques With and Without GridSearchCV," in IEEE Access, vol. 10, pp. 80151-80173, 2022, doi: 10.1109/ACCESS.2022.3165792.

[11] H. Yang, Z. Chen, H. Yang and M. Tian, "Predicting Coronary Heart Disease Using an Improved LightGBM Model: Performance Analysis and Comparison," in IEEE Access, vol. 11, pp. 23366-23380, 2023, doi: 10.1109/ACCESS.2023.3253885.

[12] M. A. Khan and F. Algarni, "A Healthcare Monitoring System for the Diagnosis of Heart Disease in the IoMT Cloud Environment Using MSSO-ANFIS," in IEEE Access, vol. 8, pp. 122259-122269, 2020, doi: 10.1109/ACCESS.2020.3006424.

[13] G. N. Ahmad, S. Ullah, A. Algethami, H. Fatima and S. M. H. Akhter, "Comparative Study of Optimum Medical Diagnosis of Human Heart Disease Using Machine Learning Technique With and Without Sequential Feature Selection," in IEEE Access, vol. 10, pp. 23808-23828, 2022, doi: 10.1109/ACCESS.2022.3153047.

[14] Y. Pan, M. Fu, B. Cheng, X. Tao and J. Guo, "Enhanced Deep Learning Assisted Convolutional Neural Network for Heart Disease Prediction on the Internet of Medical Things Platform," in IEEE Access, vol. 8, pp. 189503-189512, 2020, doi: 10.1109/ACCESS.2020.3026214.

[15] M. Alkhodari, H. F. Jelinek, N. Werghi, L. J. Hadjileontiadis and A. H. Khandoker, "Estimating Left Ventricle Ejection Fraction Levels Using Circadian Heart Rate Variability Features and Support Vector Regression Models," in IEEE Journal of Biomedical and Health Informatics, vol. 25, no. 3, pp. 746-754, March 2021, doi: 10.1109/JBHI.2020.3002336.

[16] V. Bui et al., "Simultaneous Multi-Structure Segmentation of the Heart and Peripheral Tissues in Contrast Enhanced Cardiac Computed Tomography Angiography," in IEEE Access, vol. 8, pp. 16187-16202, 2020, doi: 10.1109/ACCESS.2020.2966985.

[17] G. Wang, F. Lauri and A. H. E. Hassani, "Feature Selection by mRMR Method for Heart Disease Diagnosis," in IEEE Access, vol. 10, pp. 100786-100796, 2022, doi: 10.1109/ACCESS.2022.3207492.

[18] S. Koehler et al., "Unsupervised Domain Adaptation From Axial to Short-Axis Multi-Slice Cardiac MR Images by Incorporating Pretrained Task Networks," in IEEE Transactions on Medical Imaging, vol. 40, no. 10, pp. 2939-2953, Oct. 2021, doi: 10.1109/TMI.2021.3052972.

[19] D. Cenitta, R. VijayaArjunan and K. V. Prema, "Ischemic Heart Disease Prediction Using Optimized Squirrel Search Feature Selection Algorithm," in IEEE Access, vol. 10, pp. 122995-123006, 2022, doi: 10.1109/ACCESS.2022.3223429.

[20] R. Avanzato and F. Beritelli, "Heart Sound Multiclass Analysis Based on Raw Data and Convolutional Neural Network," in IEEE Sensors Letters, vol. 4, no. 12, pp. 1-4, Dec. 2020, Art no. 7004104, doi: 10.1109/LSENS.2020.3039366.

[21] X. J. Chen et al., "Heart Sound Analysis in Individuals Supported With Left Ventricular

Assist Devices," in IEEE Transactions on Biomedical Engineering, vol. 68, no. 10, pp. 3009-3018, Oct. 2021, doi: 10.1109/TBME.2021.3060718.

[22] A. Sengupta, K. Dutta, T. Beckie and S. Chellappan, "Designing a Health Coach-Augmented mHealth System for the Secondary Prevention of Coronary Heart Disease Among Women," in IEEE Transactions on Engineering Management, vol. 69, no. 6, pp. 3085-3100, Dec. 2022, doi: 10.1109/TEM.2020.2997662.

[23] S. Li, "Multifractal Detrended Fluctuation Analysis of Congestive Heart Failure Disease Based on Constructed Heartbeat Sequence," in IEEE Access, vol. 8, pp. 205244-205249, 2020, doi: 10.1109/ACCESS.2020.3037080.

[24] D. Bertsimas, L. Mingardi and B. Stellato, "Machine Learning for Real-Time Heart Disease Prediction," in IEEE Journal of Biomedical and Health Informatics, vol. 25, no. 9, pp. 3627-3637, Sept. 2021, doi: 10.1109/JBHI.2021.3066347.

[25] Z. Sun, Z. Sun, W. Dong, J. Shi and Z. Huang, "Towards Predictive Analysis on Disease Progression: A Variational Hawkes Process Model," in IEEE Journal of Biomedical and Health Informatics, vol. 25, no. 11, pp. 4195-4206, Nov. 2021, doi: 10.1109/JBHI.2021.3101113.

[26] L. Qiao, Y. Gao, B. Xiao, X. Bi, W. Li and X. Gao, "HS-Vectors: Heart Sound Embeddings for Abnormal Heart Sound Detection Based on Time-Compressed and Frequency-Expanded TDNN With Dynamic Mask Encoder," in IEEE Journal of Biomedical and Health Informatics, vol. 27, no. 3, pp. 1364-1374, March 2023, doi: 10.1109/JBHI.2022.3227585.

[27] A. Abdellatif, H. Abdellatef, J. Kanesan, C. -O. Chow, J. H. Chuah and H. M. Gheni, "Improving the Heart Disease Detection and Patients' Survival Using Supervised Infinite Feature Selection and Improved Weighted Random Forest," in IEEE Access, vol. 10, pp. 67363-67372, 2022, doi: 10.1109/ACCESS.2022.3185129.

[28] J. Robert et al., "Spectral Analysis of Tissue Displacement for Cardiac Activation Mapping: Ex Vivo Working Heart and In Vivo Study," in IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control, vol. 69, no. 3, pp. 942-956, March 2022, doi: 10.1109/TUFFC.2021.3137989.

[29] Y. Pei et al., "Building a Risk Prediction Model for Postoperative Pulmonary Vein Obstruction via Quantitative Analysis of CTA Images," in IEEE Journal of Biomedical and Health Informatics, vol. 26, no. 7, pp. 3127-3138, July 2022, doi: 10.1109/JBHI.2022.3146590.

[30] C. H. Lee and S. H. Kim, "ECG Measurement System for Vehicle Implementation and Heart Disease Classification Using Machine Learning," in IEEE Access, vol. 11, pp. 17968-17982, 2023, doi: 10.1109/ACCESS.2023.3245565.

[31] W. -H. Ho, C. -T. Liao, Y. J. Chen, K. -S. Hwang and Y. Tao, "Quickly Convert Photoplethysmography to Electrocardiogram Signals by a Banded Kernel Ensemble Learning Method for Heart Diseases Detection," in IEEE Access, vol. 10, pp. 51079-51092, 2022, doi: 10.1109/ACCESS.2022.3173176.

[32] Heart Disease Datasets (https://www.kaggle.com/datasets/johnsmith88/heart-disease-dataset),

[33] UCI Heart Disease Datasets (https://archive.ics.uci.edu/ml/datasets/heart+disease),

[34] Heart Disease Prediction Datasets (https://towardsdatascience.com/heart-disease-prediction-73468d630cfc),

[35] Heart Attack Analysis Prediction Datasets (https://www.kaggle.com/datasets/rashikrahmanpritom/heart-attack-analysis-prediction-dataset).

[36] Dr. M. Varadharaj. (2019). Density Based Traffic Control System with Smart Sensing Of Emergency Vehicles. International Journal of New Practices in Management and Engineering, 8(02), 01 - 07. https://doi.org/10.17762/ijnpme.v8i02.75

[37] Moore, B., Clark, R., Martinez, J., Rodriguez, A., & Rodriguez, L. Anomaly Detection in Internet of Things (IoT) Data Streams. Kuwait Journal of Machine Learning, 1(4). Retrieved from http://kuwaitjournals.com/index.php/kjml/article/view/151

[38] Kothandaraman, D., Praveena, N., Varadarajkumar, K., Madhav Rao, B., Dhabliya, D., Satla, S., & Abera, W. (2022). Intelligent forecasting of air quality and pollution prediction using machine learning. Adsorption Science and Technology, 2022 doi:10.1155/2022/5086622