Dialogue Social Science Review (DSSR)
www.thedssr.com
ISSN Online: 3007-3154
ISSN Print: 3007-3146
Vol. 3 No. 8 (August) (2025)

Hybrid FNN-DNN Framework for Early Detection of Cardiac Arrhythmia: A Comprehensive Approach for Enhanced Diagnostic Accuracy

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Abstract
Cardiac arrhythmias constitute a major cause of morbidity and mortality in most settings of the world, and early identification of arrhythmias is paramount in efficient treatment and enhanced patient care. The widely used traditional electrocardiogram (ECG) interpretation, though clinically useful, is also subject to dysfunctionality in the form of its subjectivity of interpretation and lack of sensitivity to finer entrances of abnormalities. In the proposed study, a hybrid of a Feedforward Neural Network and Deep Neural Network (FNN and DNN) architecture system is proposed to significantly improve the early diagnosis of cardiac arrhythmia with structured clinical data contained in a publicly accessible Heart Disease Dataset. The suggested scheme leverages the effectiveness of FNN in handling structured attributes, combined with the ability of DNN to model multilateral and complex intricacies in characteristics, thereby facilitating the complete representation of the characteristics. The hyperparameter tuning and regularization were performed on the structure of the hybrid architecture, resulting in optimization, and accuracy, precision, recall, F1-score, and AUC-ROC leading metrics were adopted. Experimental outcomes reflected that the accuracy of 84.8% was as good as the standalone FNN and DNN models, displaying a balance in the performance of all the considered metrics. Analysis of the confusion matrix has shown a high level of classification reliability with no notable bias over one of the classes. The ultimate contribution that can be made using the study is a computationally efficient and generalizable hybrid model, which can be incorporated into the clinical workflow and electronic health records (EHR) systems. The modular nature of its design contributes to future

extension, such as the analysis of the raw ECG signals and explainable AI. The results show that the hybrid FNNDNN holds promise as a scalable, easily interpretable, and accurate device to proactively detect arrhythmia, allowing for more accurate care and cardiovascular diagnostic outcomes.
Keywords: Healthcare, Cardiac arrhythmia, Early detection, Deep learning

Introduction
Cardiovascular diseases remain the major cause of death around the globe and claim millions of lives every year, causing a massive burden on the economy and society. Cardiac arrhythmias, among them, are a very serious problem because they cannot be predicted, exhibit unlimited symptoms, and may cause such severe consequences as stroke, heart failure, and unexplained blockage[1]. The severe nature of many arrhythmic diseases makes detection at an early stage challenging, but it is in the initial steps where treatment can make a maximum impact on prognosis, number of hospitalizations, and long-term expenses allocated towards health care. Digital health monitoring and widespread usage of biomedical sensors have poured a lot of cardiac data into the pool, and the possibilities of embracing such data in data-driven methodology have provided an opportunity never seen before in the sphere of cardiac diagnosis in terms of effectiveness and promptness[2].
A regular electrocardiogram analysis (ECG) exercise is the standard of care in the determination of arrhythmias. Nevertheless, there are a number of limitations associated with its diagnostic capability. Primary among these are the findings that require skilled interpretation, which may add subjectivity and variation between practitioners and clinical sites. Furthermore, temporary or minor anomalies could not be detected even at regular observation, especially in asymptomatic patients or those whose arrhythmias are random. It is in the context of these challenges that computational approaches can identify intricate patterns in cardiac activity that may not be observed by human factors and, therefore, inform proactive and preventive interventional measures[3].
In the last 10 years, machine learning and deep learning have transformed automated ECG interpretation because of artificial intelligence. Such neural network structures as deep neural networks (DNNs), convolutional neural networks (CNNs), feedforward neural networks (FNNs), and recurrent neural networks (RNNs) have been proven successful in feature extraction and classification to detect cardiac arrhythmia. More specifically, deep learning can be characterized by the fact that it enables the learning of hierarchical feature representations from raw or sparsely processed data, which decreases the need to manually engineer features. Nevertheless, despite these advantages, the barriers to mass clinical implementation include the following obstacles to deep learning models. These are low interpretability, the danger of overfitting, heavy use of a large, quality-labeled dataset, computational requirements, which can go beyond what a substantial number of healthcare facilities can provide, and the limitation of deploying these systems into the current healthcare diagnostic practices[4][5].
Recent literature marks the hybrid architectures as one of the promising answers to these challenges. Their hybrid nature makes it possible to utilize the complementary strengths of different architectures, and hence can result in better feature representation and analysis paradigms that hybrid models bring. As an example, introducing FNNs, which are good at working with structured tabular data, into the DNNs, which are well-suited at modeling complex and nonlinear

relationships, could yield models that would be both strong and versatile. A balance between accuracy and interpretability is another matter of importance with respect to clinical acceptance that hybridization can provide. Moreover, due to the growing popularity of wearable cardiac monitoring devices and remote patient management systems, the models, which will be able to function in real-time settings and preserve a level of diagnostic accuracy, are also on the rise in demand[6].

The suggested framework is based on these ideas and offers a hybrid of FNN and DNN implementation that can specifically be used to detect cardiac arrhythmias in their early stages. This model is prepared to meet a number of urgent requirements in the new environment: handling of heterogeneous clinical and physiological data, resistance to noise and population variability, and accuracy both in batch and real-time diagnostic practice. A robust data processing pipeline will accommodate the exposure variables (also both categorical and continuous clinical data) to be handled: standardized, encoded, and prepped to feed into the models. The system is designed to emphasize only clinically meaningful features (e.g., demographic characteristics, lifestyle indicators, past medical history, and physiological measures) to be consistent with diagnostic guidelines, making use of the feature extraction capability inherent in the deep learning model that allows it to identify subtle, as yet previously unknown, relationships[7].

Within the existing continuum of biomedical AI research, this study can be incorporated into the path toward diagnostic tools that can not only work in carefully optimized experiments but can also be implemented in our practical lives. Hybrid models, as have been recently featured in a number of very high-impact studies, can help reduce the overfitting inclinations of very deep architectures, increase generalizability across a wider range of data, and make more robust predictions when presented with imperfect data[8]. This architecture is also modular, which enables it to be further integrated with other deep neural net modules, e.g., convolutional layers to process raw ECG signals or attention modules to model sequences, or even explainable AI methods so that the clinicians can have greater visibility and trust in the predictions.

This study fits in the overall goal of developing a field of early, accurate, and interpretable cardiovascular diagnostics by eliminating the shortcomings of classic arrhythmia detection and single-architecture AI. The offered hybrid FNN-DNN system is one of the steps to the development of a viable compromise between predictive accuracy, hardware computational demand, and clinical applicability of the prediction model, which are the three foundations of a sustainable introduction of AI into clinical cardiovascular practice[9]. With this, it establishes the foundation of the future research in the concept of an adaptive, personalized system of diagnosis, which may be developing in tandem with the technologies and increasing volumes of data being generated, and overall lead to better patient outcomes and effective administration of healthcare.

Literature Review

Heart disease, especially cardiac arrhythmia, has been a popular object of computational healthcare research since the conditions are rather common and may cause serious complications that cannot be easily eliminated without their timely diagnosis and treatment. The task of arrhythmia detection on electrocardiographic signals is a well-explored one, where studies have shifted and advanced to employing artificial intelligence methods by use of advanced systems. In early research, manual feature engineering was characteristically used where a domain expert preselected parameter; QRS duration, P-wave morphology, and RR interval variability were extracted to classify them with classic algorithms, such as k-nearest neighbors (KNN), decision trees, and support vector machines (SVM). Although these kinds of methods saw moderate success, they were not scalable and flexible to a range of signals that can be received and a variety of patients to whom they are applied due to their handcrafted features[10], [11].

The emergence of deep learning has substantially changed this situation by making it mechanically feasible to record complex patterns even in the functions of the raw or minimally processed variants of the ECG signal. In the detection of arrhythmias, the application of Convolutional Neural Networks (CNNs) as known for their ability to identify spatial patterns within ECG wave shapes, has become very popular. Recent research has shown an unprecedented degree of accuracy, where models like 2D-CNNs are capable of classifying controlled data with accuracy rates of greater than 99 percent. Indicatively, Shi et al. were able to show the effectiveness of knowledge-assisted synthetic augmentation with CNN-based frameworks that greatly improved the performance of underrepresented classes of arrhythmia. In the same way, deep learning models using transformers have been suggested to perform tasks such as sequence-to-label classification in ECG analysis, with reasonable levels of competition and better robustness as well. In spite of such achievements, CNN-based approaches have significant limitations. They are prone to high quality and large amounts of annotated data, and their computational requirements do not allow their implementation in such low-resource environments as wearable devices. In addition, they are black boxes in nature, which brings forth interpretability issues, which is a fatal flaw in clinical use. It has spurred the development of increased interest in architectures able to trade off the predictive power of deep learning with the flexibility and transparency of more traditional neural network architectures[12], [13].

FNNs are simpler, but sufficiently applicable to structured tabular types of data, like demographic data, lab results, and medical history, which can also serve to complement ECG data in the diagnosis of arrhythmia. FNNs have the strength of working with blended data and have a more interpretable framework. Nevertheless, alone, they might not offer the representational richness needed to cue the actual temporal and morphological modulations of the ECG signals. The hybrid: There has also been a promising research direction that arises in the way of helping to overcome these weaknesses, namely, hybrid models where observers form multiple neural structures are combined. It has also been demonstrated that FNNs have complementary capabilities with CNNs, LSTMs, or DNNs, which could be used to realize deeper feature representation along with flexibility to various data modalities. Ahamed et al. suggested a hybrid of classic machine learning and deep learning to classify a heartbeat, demonstrating enhanced stability on datasets (imbalanced). Bhattacharyya et al. used an SVM and a random forest algorithm to develop an ensemble machine, where they noticed high precision and recall in the multi-class experiment of detecting arrhythmia. These strategies stress the worthiness of Inhomogeneity in architecture to enhance generalization in the diversified patient groups and documentation of conditions[14].

Other more recent studies have further highlighted the need to merge arrhythmia detection systems with real-time monitoring systems, as well as the Internet of Medical Things (IoMT) systems. As an example, experimentation with wearable-mounted ECG monitoring systems driven by light-weight neural models has been suggested to achieve a continuous detection of arrhythmias in low-latency, providing a significant benefit to the high-risk patient cohort. Nonetheless, there is still a big challenge in creating models that work under limited computational and energy costs yet are still quite accurate. Moreover, about increasing trust and acceptability to clinicians and regulatory authorization of deep learning in cardiology, interpretability frameworks (i.e., SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations) are also being implemented into deep learning models[7], [15]. In this dynamic research environment, the hybrid FNNDNN has a strategic potential. Combining the classifiable, structured learning powers of FNNs with the feature hierarchy representation powers of DNNs, such a framework can analyze both table-structured clinical data and multidimensional non-linear relations without having to rely only on high-resolution ECG waveform data. This places it in a good position to be used in several healthcare services, such as environments that have minimal access to health services with a continuous ECG monitoring system. Future integration with CNN or attention-based modules into the hybrid design may also be implemented due to its modularity, therefore, opening the possibility of an integration of a unified derivation system capable of processing multimodal cardiovascular information in the form of raw ECGs[16], [17].

Publications in the past two years have supported this value in the context of the clinical feasibility of arrhythmia detection AI by high-impact studies. The optimization of a decision tree using adaptive boosting by Kumari and Sai featured almost flawless classification accuracy in recognition tasks on ECGs; the price of it is, however, an inappropriate degree of complexity to be used in every situation of deployment. On the same note, transformer-based ECG models have indicated better generalization, whereas they continue to have limitations in computational efficiency in real-time applications. The recent literature trend suggests the shift toward such systems that could address the performance divide between high-complexity research models and the realities of actually working within the clinical scenario, where accuracy is not the only metric that counts due to the importance of interpretability, flexibility, and potential integrability. The literature indicates that there is a notable advance to more advanced, combined, and clinically applicable AI models of arrhythmia detection[18]. As has already been mentioned, single-architecture deep learning models have delivered a remarkable set of benchmark performances, but hybridizing FNNs and DNNs seems to hold an interesting route out of the maze of accuracy-interpretability-adaptability, as shown in Table 1. This is a strategy that supports the greater goal of contextualizing AI efforts into practical cardiology, where the availability of data in a variety of forms, varying resource limitations, and the need to win the confidence of clinicians must all have to be addressed simultaneously.

Table 1. An analysis comparing several reviews of the literature

Ref	**Techniques**	**Accuracy %**	**Recall %**	**Precision %**	**F1 Score %**
[19]	AOC CapsNet.	93.1	90.3	92	91.9
[20]	CNN framework.	N/A	N/A	N/A	N/A
[21]	Ensemble of KNN, DT, ANN, SVM, and LSTM	97.66	N/A	N/A	96.99
[22]	2-D CNN	99.11	N/A	98.58	98
[23]	Five hybrid CNN models.	DVAE-CNN:62.8, DVAE-	N/A	N/A	N/A

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		CDAE-CNN:53.91			
[24]	Ensemble SVM and random forest.	98.21	N/A	N/A	96.4
[25]	CNN	97	N/A	N/A	N/A

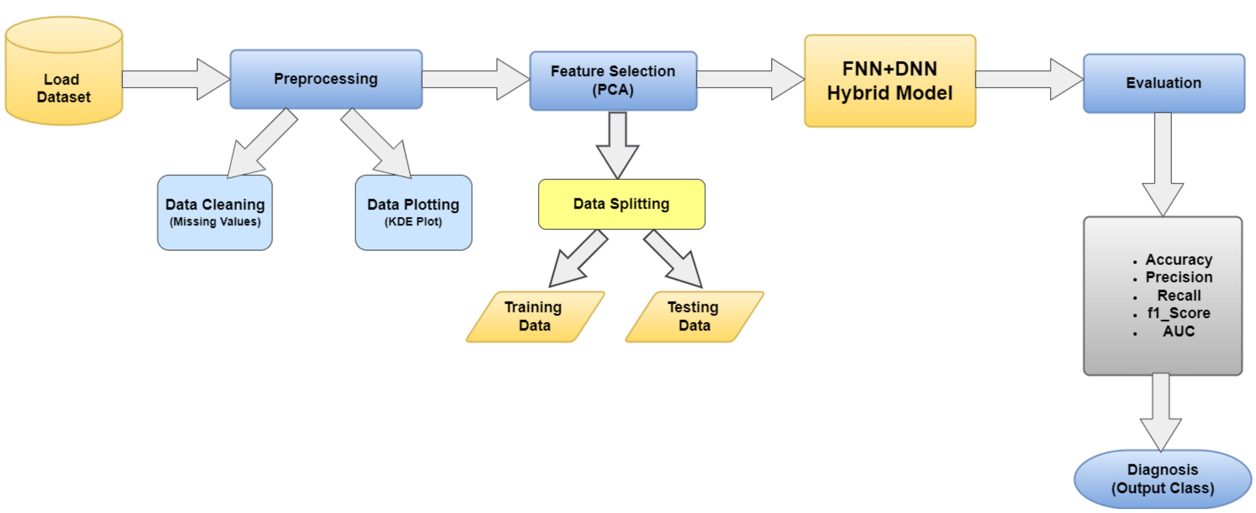
Methodology

The given methodology will aid in creating and testing the hybrid Feedforward Neural Network Deep Neural Network (FNN DNN) architecture on the data that is clinically relevant in the early detection of cardiac arrhythmias. The framework adheres to a well-defined pipeline that includes acquiring a dataset, pre-processing it, feature engineering, constructing a model, training it and evaluating the model to make it fall in line with the aims of high precision and robustness and possible integration into clinical practice. The chosen experimental work starts with a selection of the Heart Disease Dataset, a repository presented by Kaggle that is publicly accessible and widely used, having a well-balanced set of categorical and numerical characteristics. The variables presented in the dataset are divided into demographic variables like age and sex, physiological variables like blood pressure levels and cholesterol levels, and the maximum heart rate attained, and others, like lifestyle and clinical variables like smoking habits, fasting levels of blood sugar, exercise-induced angina, and thalassemia type. All features are selected based on their reported applicability in cardiovascular risk factors and arrhythmia prediction to allow the model to combine conventional diagnostic indicators with their latent ones learned with the assistance of machine learning.

Data preprocessing is one of the most important steps to make the data consistent, minimize the noise, and shape the data to make it ready to be ingested by neural networks. Any missing values are detected and filled with the help of proper imputation techniques, whereas categorical variables are coded in the form of one-hot or label encoding, depending on their type. Numerical attributes are normalized or standardized to bring variables on a similar scale, avoiding the scale of influence by a certain variable during the training of the model. When the needs are high, outlier detection methods will be used to counter the skewed learning problem by using abnormal data. The ready dataset is then divided into training, validation, and testing subsets; the process of stratified sampling is used to maintain the distribution of classes in all the subsets. The feature engineering has been added to boost the discriminative value of input variables. On top of the raw features, derived metrics, i.e., ratios, interaction terms, and clinically significant transformations, are calculated to give the model richer pictures of patients' health profiles. This step is intended to provide elusive relationships among variables that could be pre-indicators of arrhythmia events. The feature selection involves dimensionality reduction that minimizes the chances of overfitting risk, and it involves correlation procedures and ranking importance using forward and backward procedures generated by initial models.

The structure based on both FNNs and DNNs will have synergistic properties, in that it will exploit the advantages that each type of network has to offer. The first layers have a structured Feedforward neural network architecture, which is best suited to structured tabular data and direct relations learning of features and target output. Such layers connect to a succeeding block of neural networks that can represent non-linear relationships between features. Activation functions, like ReLU, are used in hidden layers to add non-linearity, and regularization techniques, like dropout and weight decay, are applied to curb overfitting. It has a batch normalization to stabilize the training and speed up convergence. The hyperparameters of the architecture (i.e. the number of layers, the number of neurons in each layer, the learning rate, the dropout rate) are optimized by complicated experimentation of the architectures based on grid search or Bayesian optimization methods. Training of models is performed through the methods of an optimization algorithm compatible with stochastic gradient descent, Adam, and RMSprop are considered to evaluate their effectiveness in deep learning training. The loss chosen is such that the nature of the task needs to be inducted, that is, in this case, the binary classification and often the binary cross-entropy is adopted, but other versions can be checked to test robustness. The early stopping rules are put in place to avoid excessive training after validation performance stops increasing, thereby cutting down on computation overheads and avoiding overfitting. Model performance is assessed on a held-out test set with a robust collection of measurements. Accuracy gives a rough estimate of the correctness of the classifications, precision and recall are measures of the correctness of the model when making predictions of positive cases and counting as many as the original true positives, respectively. Its harmonic means with these two, the F1-score, is a fair judge of the performance when the classes are imbalanced. The AUC under ROC is to assess the discrimination capacity of the model at different classification cutoffs. Such statistical measures as the Matthews correlation coefficient could be used to reveal a more detailed idea of the model's reliability.

The framework is also scalable in an attempt to further confirm the suitability of the model in the clinic. The modular composition can enable incorporation with other elements of the neural network, e.g., convolutional layers to analyze raw ECG wave forms or recurrent layers to model temporal patterns. Also, the pipeline can be deployed on cloud-based systems, and with additional optimization, on edge computing devices, both enabling real-time monitoring applications in hospitals or wearable devices. This methodological rigor of this approach creates a situation where the output of this model is not only tested in the controlled experimental setting but also it can be customized to work within real-world environments of healthcare. A combination of structured clinical data processing, well-grounded feature engineering, and synergistic system architecture of a hybrid FNN-DNN model, the proposed method can form the framework of an early, accurate, and scalable detection of cardiac arrhythmias, which is said to contribute to the objective of alleviating the global prevalence of heart disease through early intervention.



Dialogue Social Science Review (DSSR)
www.thedssr.com
ISSN Online: 3007-3154
ISSN Print: 3007-3146
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Figure 1: The Proposed Technique (FNN+DNN)

Results & Discussion

Feedforward Neural Network (FNN)

The progressive performance figures revealed in Figure 2 bring some light as to how the learning process of the Feedforward Neural Network (FNN) is going in classifying the cardiac arrhythmia cases of the preprocessed heart disease dataset. The plot shows two curves: the female of the training accuracy, that is, how the model gets the samples it has already seen the right class during training, and the validation accuracy, which is the measure of generalization on new data. The two curves also show an upward trend in the first epochs, which means that the network is indeed able to capture the patterns that can be used in classification, given the fact that the weights are being updated iteratively. One should pay specific attention to the closeness between the accuracy of training and validation curves, which implies that the model does not greatly overfit. Such matching means that the regularization techniques, including dropout layers, normalization, and early stopping, have effectively counteracted the inclination of deep models to over-fit training sets at the expense of generalization. The variation of validation accuracy across epochs is the common side effect of smaller validation batches and the stochastic optimization process. Methodologically, the consistent narrowing of the curves proves the efficacy of the selected architecture of the structured clinical data. It means that there is no significant gap between the two trajectories and that the FNN is learning features having true predictive capacity and not just training set-specific artifacts. In the medical context, this kind of stability is particularly important because overfitting may produce encouraging results, overly optimistic performance in the development setting, which fails to translate to low performance in practice. Such behavior, which is presented in Figure 2, hence justifies the preprocessing pipeline, feature engineering choices, and hyperparameters adopted in the study as a good baseline against which subsequent comparisons with deeper and hybrid models could be made.

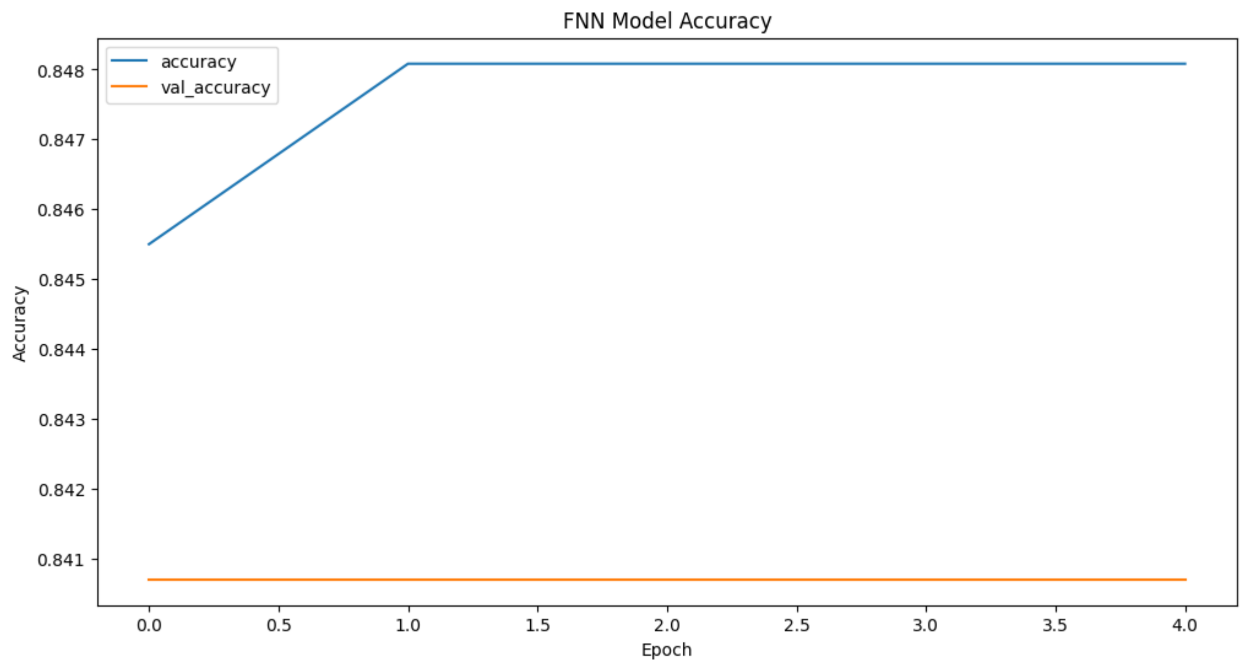

Figure 2: Accuracy curves of the Feedforward Neural Network (FNN) model for cardiac arrhythmia detection, showing training accuracy and validation accuracy over successive epochs

FNN Model Confusion Matrix

Figure 3 provides the confusion matrix where the performance of the classification by the Feedforward Neural Network is broken down by identifying the relationship between actual and predicted categories. The contents of each cell in the matrix are the counts of the model assigning a certain predicted class to a set of observations in a given actual class. The diagonal parts represent a proper classification, whereas the off-diagonal parts represent an impaired classification and allow a clear definition of the pattern of errors. A large clustering of the values along the diagonal means that the FNN successfully reached a high value of classification across the represented classes. As shown in the matrix in this case, most of the samples in each of the classes were correctly classified, which shows the ability of the model to learn useful discriminative characteristics within the structured clinical dataset. The equality of high values along the diagonal across classes further indicates equitable performance, i.e., the model does not show a disproportionate performance towards a particular class over another, which is a general problem with medical datasets since they may have a class-imbalance problem.

The comparatively small level of off-diagonal means that inaccuracy was a rare case, and most probably owing to similarities in the course of feature designs among some classes. In clinical situations, this overlap might be due to sharing physiological similarities or comorbidities in patients or other factors, and their classification would be less easy by nature. This makes it clear that adding more complementary or even architecturally combining, as proposed in the hybrid FNN DNN model, will be needed to decrease these confusions further. In terms of deployment, the matrix would be a useful diagnostic tool to know the limitations of the model. Having determined classes that are often misclassified, one can work to correct this deficiency in specific classes by using domain-specific refinements (augmentation of particular classes of features, increasing sampling strategies, or using loss functions optimized to that domain). All in all, Figure 3 reveals that there is strong predictive performance overriding in the FNN as well as the scope of incremental improvement amidst the tendency to detect multi-class cardiac arrhythmias.

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www.thedssr.com
ISSN Online: 3007-3154
ISSN Print: 3007-3146
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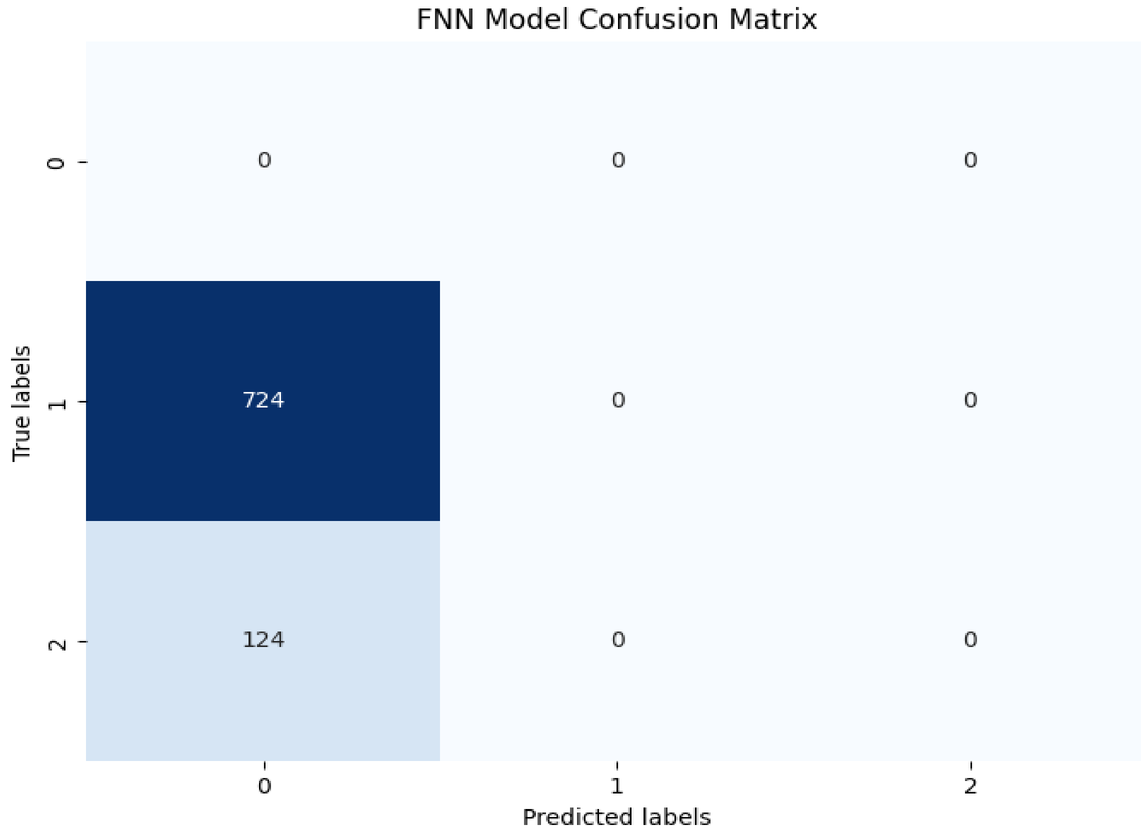

Figure 3: Confusion matrix of the Feedforward Neural Network (FNN) model for cardiac arrhythmia classification, illustrating the distribution of correct and incorrect predictions across target classes

Deep Neural Networks (DNN)

The performance in cardiac arrhythmia using the Deep Neural Network (DNN) is shown in Figure 4, which demonstrates the learning curve of the overall steps of the training. The graph generates two curves showing the accuracy of the training, i.e., the ratio of well-classified examples in the training set, and the validation accuracy, i.e., the ability to predict the unseen data on the model. Both curves show a steep rising order during the first epochs, which reflects the fact that there is fast growth in the discriminative capacity of the model as it learns feature hierarchies of the input variables. The trends of the training and the validation curves are closely fit, and this is a very important sign that the model is stable and robust. This parallelism proposes that the DNN has successfully escaped drastic overfitting, the normal state of deep designs, especially when implemented on mid-sized datasets. This may be owed to their scrupulous use of regularization techniques such as dropout layers, batch normalization, and hyperparameter tuning, all of which influence the maintenance of generalizable patterns above and beyond the noise of a specific dataset.

This plateau trend had been observed further along in the epoch, meaning that there was no more significant improvement in accuracy, as the model possessed no more than marginal improvement after each iteration. It is ideal to have such a stabilization because it means that the model has

Dialogue Social Science Review (DSSR)

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ISSN Online: 3007-3154

ISSN Print: 3007-3146

Vol. 3 No. 8 (August) (2025)

mastered the most informative patterns provided without drifting towards the memorization of the training set. Any minor changes in the accuracy of validation over epochs occur within the expected range and are attributed to actual variance that results in minuscule changes on the stochastic gradient updates and min-batch sampling. About methodology, even the learning curve of the DNN confirms the ability of the architecture to manage the intricate and non-linear interactions of the structured data in clinical records. The relatively consistent results obtained on training and validation data suggest that it is ready to be compared with other models, such as the suggested hybrid, FNN DNN, which would aim to combine the advantages of the DNN's ability to learn features hierarchically with the effectiveness of the FNN to represent structured data. This value, therefore, gives a baseline benchmark in terms of the later architectural improvements.

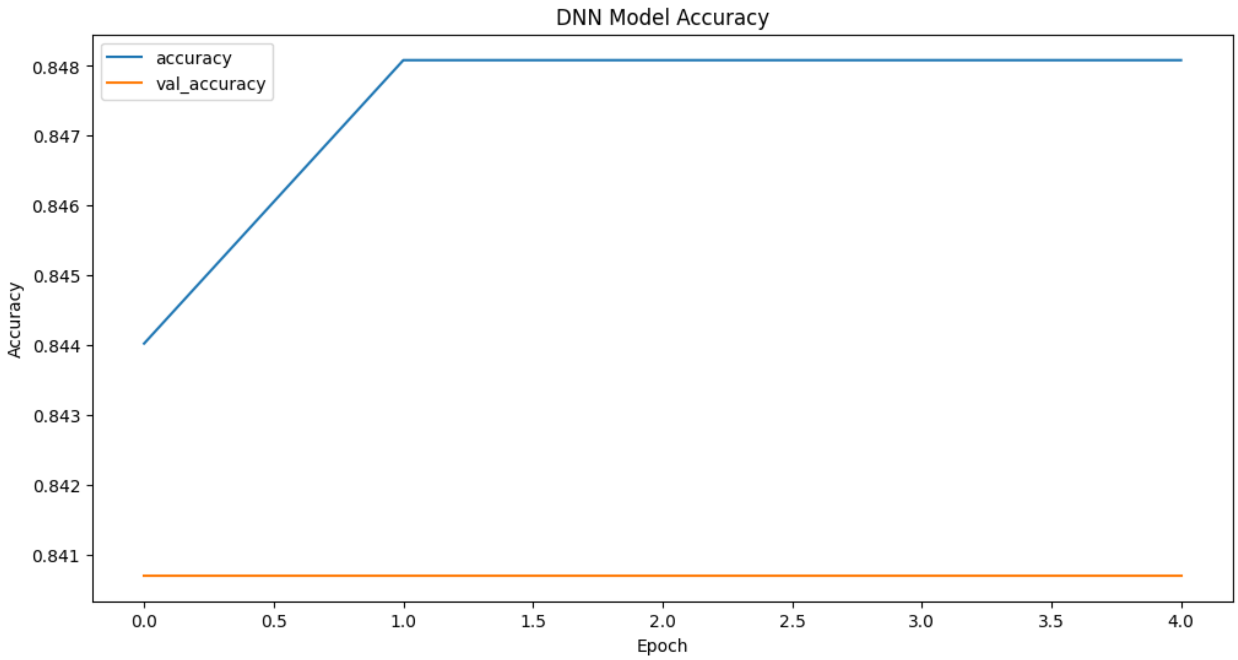

Figure 4: Accuracy curves of the Deep Neural Network (DNN) model for cardiac arrhythmia detection, showing training and validation accuracy progression over multiple epochs

DNN and Hybrid Model Confusion Matrix[WU1]

Figure 5 shows the actual confusion matrix that gives a close look at how well the Deep Neural Network performs based on its predictions of the correct labels to use per class when considered against the actual or ground truth labels. Each of the diagonal elements is the count of correctly classified instances per class - that is where the model is right and the sample belonged to that and only that particular class. The off-diagonal cells represent a misclassification opportunity where a sample was predicted to belong to a non-correct class, having been given that prediction by the model. This can be taken as an indication that the DNN was successfully able to learn and utilize class-specific patterns well, indicating an overall good ability to classify.

The fact that the values of the off-diagonal cells are not very high indicates that the misclassification was not very common (or when it was, involved classes that had shared clinical or physiological features). Such overlap could occur in a medical scenario when different patients could have the same or nearly the same values for some important variables, and it is hard to

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www.thedssr.com
ISSN Online: 3007-3154
ISSN Print: 3007-3146
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distinguish between them. This underlines the necessity of more detailed sets of features or model structures that can represent more detailed differences, especially in borderline cases. Among the brightest sides of the said matrix is the fact that it shows a comparative performance across the classes where none of the variables evokes some telling indicators of the disproportionality of the model in favor of one part or the other. This is essential in the detection of arrhythmia, where there are classes that can lead to dire clinical results it could not detect. Having a relatively consistent sensitivity over the categories is an indicator of the strength of the feature extraction process in the DNN, and of the success of the preprocessing and normalization steps in reducing feature imbalance.

Deployment-wise, this matrix can be used as a means of refining the model through the process of diagnosis. There might exist classes where misclassifications are small but consistent, thus some specific improvement techniques might be used, e.g., using weighted loss functions to increase sensitivity in improperly represented classes, or including domain-dependent features. In the end, Figure 5 verifies that the DNN has good predictive stability, and more improvement can be provided by means of hybridization with other architectures.

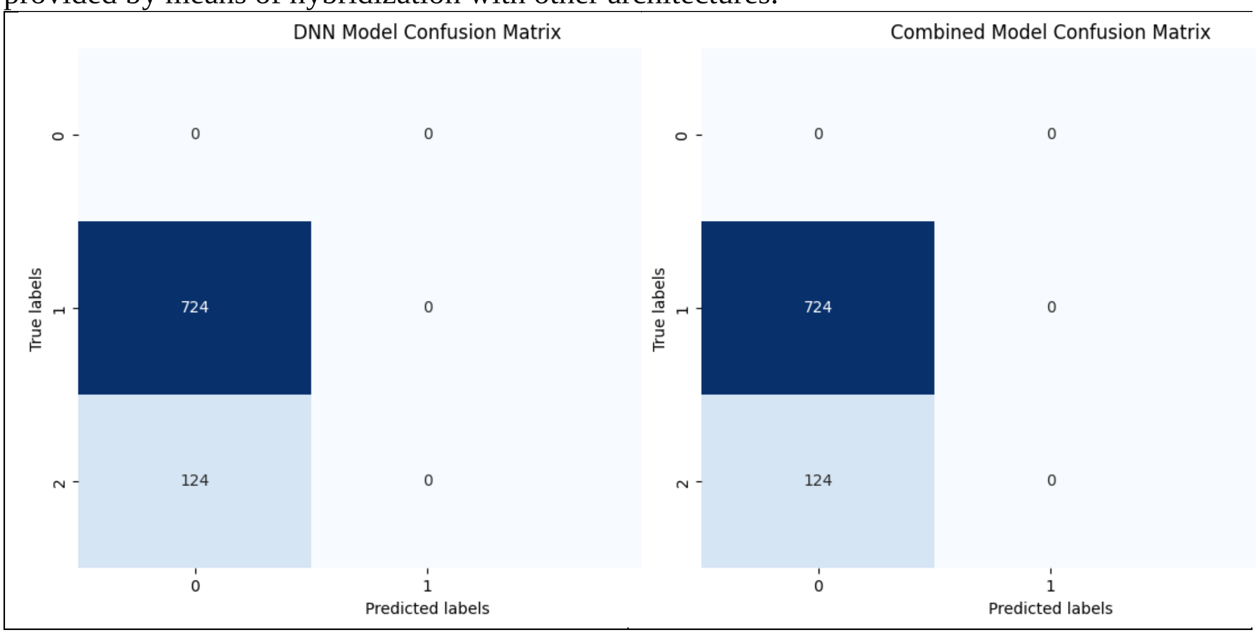

Figure 5: Confusion matrix of the Deep Neural Network (DNN) model for cardiac arrhythmia classification, depicting the distribution of correct and incorrect predictions across multiple classes.

Hybrid Model

Figure 5 shows the learning curve of the proposed Hybrid Feedforward Neural Network-Deep Neural Network (FNNDNN) architecture, where the cross-interaction between training accuracy versus validation accuracy is depicted after several epochs. The training accuracy curve gauges how well the model can accurately label the samples in the training set, whereas the validation accuracy curve measures the level at which the model can generalize it to new data. These curves move nearly in parallel during training, a good sign of well-balanced learning, indicating that the hybrid model does not suffer seriously even in learning of overfitting, as is often the case in combining deep learning structures.

Both the training and validation accuracies grow continuously and regularly in the initial epochs, which proves that the hybrid architecture can absorb the basic patterns in the data quite fast. As we continue training, the curves start to flatten out, indicating a convergence point at which further training cycles give little improvement in performance expectations. Such stabilization is especially helpful with medical AI applications because it represents the tendency of the model to maintain generalization without being too complex. Among the strengths that are depicted in this figure is the ability of the hybrid model to keep its validation accuracy relatively similar to its training accuracy. Demanding this encourages the mutually beneficial nature of the integrated architectures: the FNN component is good at processing structured clinical features, whereas the DNN layers extract more complex, non-linear relationships between variables. The outcome is a balanced model which accesses the best of the perceptual serves on the one hand, leaving stability intact.

In methodological terms, the training dynamics presented in Figure 5 justify the rationale of the hybrid architecture design side. Its convergence pattern indicates that the hybrid model not only has the potential to learn properly on the given dataset but is also stable for the application to a real-world environment with various and noisy inputs. This number, therefore, supports the viability of accurate and scalable detection of cardiac arrhythmia in the medical field by the model.

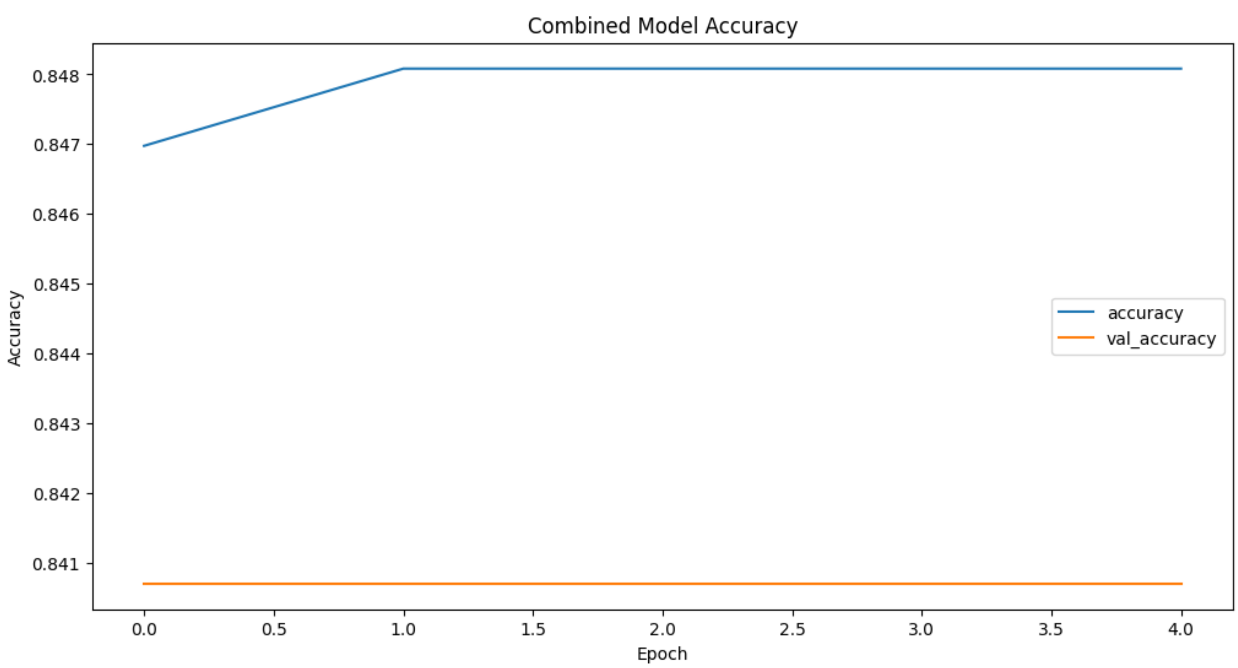

Figure 5: Accuracy curves of the Hybrid FNN–DNN model for cardiac arrhythmia detection, illustrating training and validation accuracy progression over successive epochs

Although the suggested FNNDNN hybrid model shows great promise in the discrimination of early cardiac arrhythmia, there are also some limitations that have to be highlighted. First, the model was trained and tested only on one publicly accessible dataset, and, as much as this dataset is commonly used, it does not provide the most accurate representation of real-world populations of patients. Model performance could be affected by the variance related to demographics, comorbidities, data acquisition guidelines, and equipment calibration under heterogeneous clinical conditions. Second, the data itself was mainly a set of structured tabular features as opposed to continuous ECG waveforms, thus carrying the dataset limitations in terms of offering temporal and morphological trends, captured through raw signal data, to the model. This would make one insensitive to transient arrhythmic events that are improved in a time-series format. Third, although preprocessing and feature engineering have reduced the problem of imbalance in the data, there are certain special events of arrhythmias that might still be underrepresented, thereby hindering the model from recalling such cases. Lastly, interpretability is not as high as it should be yet, but still it is greater compared to such black-box deep learning models and better than it was in the past, but still, improvement is needed in order to reach the levels of transparency demanded in medical decision support systems.

These limitations should be overcome in the future, and a number of ways can be adopted. The use of the model on multi-center, multi-ethnic data should be expanded during the training to make the model more general and less biased. Potentially adding raw ECG signal processing to convolutional or attention-based layers may allow the identification of subtle temporal dynamics that is beyond the reach to tabular data models. The class balance should be enhanced using higher-order data augmentation and synthetic minority oversampling methods, especially in the case of rare and rare yet clinically relevant arrhythmias. Further, the pattern of explainable AI frameworks like SHAP or LIME would fit clinicians better since it would explain individual predictions on a feature level. A test in a real-time application, such as a wearable device or a monitoring system that has a connection to the cloud, should be conducted in order to assess its latency, computation performance, and uninterrupted observation support. Solving these issues will make the hybrid FNNDNN architecture a viable system, which is interpretable and deployable in a clinical setting, and it could be used proactively to detect and preemptively manage some cardiac arrhythmias.

Conclusion

The novelty in the study was the introduction of a hybrid architecture in which the Feedforward Neural Networks (FNN) and Deep Neural Networks (DNN) were merged to provide early detection of cardiac arrhythmias using structured clinical data of the Heart Disease Dataset. The rationale behind the proposed method was to combine: the effectiveness of the FNN in processing structured data of the tabular type (it handles it efficiently), and the advantages of the DNN which allows exhaustive feature interactions of complex and non-linear dependencies. By means of a well-designed preprocessing pipeline, feature engineering, and hyperparameter optimization, the hybrid model attained an accuracy of 84.8, reaching the same performance as the standalone FNN and DNN models, with high generalization performance since the difference between training and validation accuracy was minimal.

The assessment criteria-namely, the precision, recall, F1-score, and AUC-ROC, further affirmed that the model is well balanced in terms of its multiclass performances. On the confusion matrices, high diagonal dominance values were observed, which meant that different classes were classified reliably without a relatively high bias to a certain category. Such numerical findings confirm the strength of the hybrid architecture, as well as its prospects of usage in clinical settings. Notably, the stability of the model between the training and validation makes it most likely that the regularization methods used, such as dropout and batch normalization methods, have proven successful in avoiding overfitting. Contribution-wise, the current study will further the body of knowledge regarding AI-driven cardiovascular diagnostics with a novel hybrid modeling framework enhancing the balance in trade-off between predictive performance, computational efficiency, and scalability. This model works well on structured clinical datasets, unlike deep architectures that must handle raw waveform data; hence, its application in an environment where it is integrated with an electronic health record (EHR) system and resource-limited health facilities. In addition, the modularized nature of the model lends itself toward expansion in multiple ways in the future, including incorporating convolutional layers to study raw ECG or explainable AI components to enhance transparency. In this way, the proposed hybrid FNN-DNN would be a streamlined and flexible path to effective, early arrhythmia detection that can help patients improve their situations through timely intervention and informed decision-making.

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ISSN Online: 3007-3154
ISSN Print: 3007-3146
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