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COMPREHENSIVE ANALYSIS ON INTELLIGENT DEEP LEARNING BASED APPROACHES FOR HEART BEAT DETECTION

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ABSTRACT

In recent years, the research study on heartbeat detection has been increased, which is more essential in medical and sports-related applications. These analyses help to find most heart disorders by examining the electrical signal of the heartbeat that produced with distinct unique cardiac tissues located in the heart of the body. Recently, numerous works have been developed to generate class labels based on automatic heartbeat classification techniques. More importantly, Deep Learning (DL) approaches used in recent times to optimize the functionality of traditional heartbeat methodologies. With this motivation, this study analyses the DL methods of ECG-based automatic heartbeat abnormalities detection through analyzing the ECG signal pre-processing to improve the quality, heartbeat segmentation techniques to identify the target region, feature extraction methods to reduce complexity of classifier by reducing the number of resources, and different DL based classification algorithms to generate class label for identifying the heartbeat. Finally, this analysis focus on the difficulties that DL models encounter and suggest some potential future directions. The results observed from various studies clearly show that classification performance improves even when using datasets with limited sample size. This study suggests that further attention should be paid to enhancing the generalizability of DL models used to analyse ECG signals, particularly by extracting more significant sample datasets.

Keywords:-*Heartbeat Measurement; Electrocardiogram Signals; Cardiovascular Diseases and Deep Learning*

1. INTRODUCTION

The heartbeat is the most direct evidence of cardiac activity and is an actual physiological occurrence of the human body. The pulse can reveal a range of abnormal states, such as age and lifestyles behaviours, including hypertension, bundle branching or atria and ventricles obstruction, and premature atrial or ventricle contraction [1]. Electrocardiogram (ECG) represents the operational status of the heartbeat instantaneously and could be used to identify and diagnose cardiovascular diseases (CVDs). This monitoring and a typical twelve-lead configuration consists of pressurized fringe leads (3), limb leads (3), and thorax leads (6) are used to get an ECG report for the patients with heart problems. The sinoatrial node initiates a

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whole heartbeat procedure by depolarizing the atriums and ventricular and repolarizing the left ventricle, with P wave formed through atrial depolarization, ventricular depolarization creating a QRS complexity wave, and finally T wave generated using ventricular hyperpolarization [2].

In India, the high case fatality number of deaths attributable to CVD is the largest in Tamil Nadu, at around 360-430/100,000. By 2025, India is predicted to have the highest per capita rates of diabetes and obesity, with CVD being the leading cause of mortality [3]. In 2019, video conferencing and mobile healthcare began to expand quickly, leading to widespread usage and awareness of ECG signals for auxiliary symptoms of heart disorders [4]. Before ECG data [5], component application and retrieval of the content [6] and sophisticated classification methods [7] have been the subject of much prior work on these additional diagnostics.

The primary activity of ECG signal reduction is to remove noise so that an actual diagnosis may be made. The feature analysis methods such as morphological features, domain feature analysis based on time frequency, and depending on statistical evaluation have mainly utilized based on Heart Rate Variability (HRV) and also discrete wavelet transform (DWT) to gather and analyses ECG data. For example, an analysis in [8] developed several transfer function systems that are based on ECG morphologically and used them to quickly identify Atrial Fibrillation (AF), whereas in [9] reminds, distinct heartbeat groups using specific HRV measures. A quick transformation function and spectra concentration analysis of ECG recordings were used in [10] to classify heartbeats in AF by identifying frequency patterns with extremely low, low, or superior properties. In Fig.1 shows the heartbeat cycle in an ECG [11].

Several ECG signal classification methods have been developed using machine learning methods, which supports the automated identification of various cardiac disease conditions. The Support vector machine (SVM) technique [12], the data mining (DM) methodology [13], and the DL technique [14] utilized to improve an ECG classification algorithm, where the six class label generated based on the cardiac disorders [15]. On the top of Fig.2, two techniques are displayed such as ML and DL that define feature extraction process on raw ECG data, ML use feature extraction based on the experts, named as “expert functionalities,” and organize selection rules whereas DL can automatically extract the features.

As an alternative, an effective DM learning of supervised neural models having flexibility and skills processed structure design is used to extract features eventually and autonomously. Several studies proven that automatic extraction of features using image processing techniques that are beneficial than expert functionalities based ECG features [16]. Consumers can utilize smartphones to keep track of their cardiac problems using automatic ECG-based arrhythmia exposure when it is convenient to eliminate the need for clinicians to assess individual indications. A heart rhythm can be identified with the use of an electrocardiogram, the most commonly used technique for identifying the heartbeat over time. With electrocardiogram leads, the electrochemical charge of the heart can be analyzed from many angles and locations to detect illness and identify diseases. Since cardiovascular illnesses have a high mortality rate, it is crucial to detect and classify arrhythmias early and accurately [17].

Dysrhythmias is detected using the heart and other anatomical features (along with spatiotemporal relationships between changed genetic variables). Some monitoring cure results may be false. This part gives a glimpse of the changed rhythms. It should be emphasized that the material provided is based on the typical healthy adult. Age, ethnicity, and gender affect ECG arrhythmia’s diagnosis factors and their characteristics and consequences. The research in [18] demonstrated an overview of arrhythmias where two or three ECG classifications are focused with distinct cardiac disease classifications and thus it is more challenging to associate and restricting the applicability of the resultant diagnostic representations.

Furthermore, like mobile health care technology advances, a considerable amount of data from wearable technology is collected. Researchers cannot simply chase excellent productivity while ignoring the challenge of computing complexities, given the desire for intel wearable equipment for quick detection and characterization. A perfect algorithmic model’s velocity and computation cost should indeed be balanced. As a result, a mathematical hurdle for rapid and reliable illness diagnosis is presented. A deep CNN for automated diagnosis was designed and tested on three distinct databases to investigate and accomplish the classification of several cardiac disorders. In this study, DL applications in cardiology were discussed in structured information, signals, and neuroimaging techniques connected to heart and vascular architecture.

Focus of this Survey: The objective of this heart beat detection based on AI is to examine existing research on transfer learning in ECG diagnosis using four common machine learning algorithms:

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stacking auto-encoders, deep belief networks, CNN, and recurrent neural networks. The process, construction, and implementation of the programs were initially discussed. Hence their uses in ECG interpretation are discussed in detail, noting their benefits and drawbacks. The section basically of this research expresses the authors' opinion on the potentiality of transfer learning in ECG diagnostics. Table 1 shows the classifications, the pulse numbers, and samples of waveform for each class in the cardiac statistics.

2. APPLICATIONS AND REVIEW FOR HEARTBEAT DETECTION

A detailed investigation of heartbeat diagnosis from simple DL techniques and more complicated network algorithms has been performed. The arrhythmia research is outlined under DL architectures, and many of these approaches are applied to the arrhythmia dataset, with the outcomes reviewed. This review section divides into two parts: DL and hybrid DL-based heartbeat detection methods.

2.1. Deep Learning-Based Heartbeat Detection Methods

Abdalla et al. used the DL method to build a unique method for automatically identifying ten distinct tachycardia types [20]. As a result, the CNN method based classification produces ten different arrhythmia types. Developing a DL-based diagnostic system for heart disease diagnosis is offered an accuracy of 99.84 percent, and it was discovered that the current method outperforms existing CNN-based algorithms.

An eleven-layer deep CNN framework used by Acharya et al. [21] to evaluate Congestive heart failure (CHF) that requires very little preprocessing of ECG data and does not require any artificial attributes or classification. The developed 11 layer deep CNN model included a diagnostic tool for cardiologists that can allow more substantial scientific ECG signals with faster reading. Thus achieving 98.97 % of higher accuracy, 99.01 % of high specificity, and sensitivity of 98.87 %. The proposed model was trained and tested using four different sets of data. In another work, 9-layer deep CNN model used by Acharya et al. [22] to detect five various sorts of the cardiac cycle in ECG data manually and obtained 94.03 % of high diagnosing accuracy in normal ECGs and 93.47% in noise-free ECGs using enhanced data. Due to the limited training data, the average result obtained by deep neural network (DNN) models is slightly better than the limited training data; the average outcome obtained by the DNN model is marginally better than existing methods. However, DNN indeed showed tremendous promise for clinical applications.

In another work, two efficient and robust panoramic fusion architectures implemented by Ahmad et al. [23] for ECG classification such as Multimodal Image Synthesis (MIS) and Multimodal Feature Synthesis (MFS). This work used Gramian Angular Field (GAF), Markov Transition Field (MTS) and Recurrence Plot (RP) to turn raw ECG data into three distinct visuals. By performing fusion initially in MIS by integrating three imaging methods into an image representation paradigm used in the CNN. Finally, multimodal fusion of modalities improves classification performance outcomes by 99.7% compared to using the modalities independently. Alqudah and Alqudah utilized [24] DL approach focused on the beat-wise analysis of ECG signal processing using the iris frequency spectrum to identify 17 kinds of ventricular tachycardia. Aberrations can be detected automatically by analyzing each ECG heartbeat. This proposed model used to provide a faster DL method for classifying ventricular arrhythmias. The described method was effective, simple, and fast according to the data, making real-time classification possible with an overall recognition accuracy of 99.13 %. When compared to earlier research, this model was promising, outperforms many others, and has the potential to be valid.

Burrello et al. utilized a robust DL-based technique for PPG-based heart rate (HR) estimation [25] on PPGDalia, that attained low Mean Absolute Error (MAE) of 3.84 Beats per Minute (BPM), outperforming the prior basic. Additionally, the models generate a large number of Pareto optimum clarifications and executed on a low-power commercial microcontroller (STM32L4) in the field of complexity vs accuracy. Generally, Neural Infrastructure Retrieval is used to construct a varied collection of Temporal Convolutional Networks for heart rate estimation. ActPPG is an adaptive algorithm that selects various heart rate estimation techniques based on the number of MAs to ensure sustainability. Chang et al. developed Deep Heart, a new HR estimate technique based on neural denoising and frequency band standardization. Deep Heart uses labelled training data to create clean PPG pulses from ECG measurements [26].

DeepHeart outperforms two existing algorithms such as TROIKA and Deep PPG, with an average absolute error of 1.98 bpm. Yet, effective HR estimate from tainted PPG data is challenging because of motion distortions induced by the user's physical activity. Deevi et al. introduced a deep representation learning strategy for ECG signal classification, which may significantly minimize the load and time spent diagnosing heart diseases by a Cardiologist that consists of denoising blocker and heartbeat classification block. Learned in the classroom approaches were used in both stages to achieve the objective [28]. The recommended technique for beat-by-beat classification into ten unique kinds of heartbeats evaluated the usage of PhysioNet's Database of MIT-BIH Arrhythmia. According to the findings, this approach can provide full-size predictions and outperforms the opposition on essential criteria.

Degirmenci et al. introduced a DL method for detecting abnormalities in ECG data. This model used a CNN trained on two-dimensional (2D) ECG signal images to classify arrhythmias [29]. The experimental findings reveal that this approach's classification performance achieved high accuracy with 99.7%, sensitivity of 99.7%, and 99.22% of high specificity within the classification of five separate ECG arrhythmias. Finally, this method provides an easy and reliable automated arrhythmia detection methodology for ECG arrhythmia classification. Dokur and Lmez utilized CNN method by utilizing the dispersion measure to select the greatest values according to rank the features by relevance [30]. ECG signal training in the form of frames takes substantially longer than training in the form of 1D signals, for both networks' training and testing periods were shown to be relatively speedy. Furthermore, by adopting small-size networks, average accomplishment rates of 99 percent achieved for all heartbeat class lables.

Ganguly et al. utilized to automate the classification of heart beat using ECG signals using LSTM structure. Furthermore, bilateral LSTM (bi-LSTM) based feature extracted and utilised for segmented ECG signal, with acceptable features using a linear motion treated multifractal order derivative assessment [31]. Even though this technique has proven highly efficient in heartbeat classification, it still has to be tested on a larger dataset. ECG DETR, a revolutionary transformer-based computational modelling multilayer perceptron utilized by Hu et al. detects arrhythmias on ECG data [32]. As per the findings, the utilized technique performs similarly to earlier studies that considered both heartbeat segmentation attained 99.12% and classification and attained overall accuracy of 99.49 percent. Huang et al. presented a two-dimensional deep CNN technique for ECG arrhythmia classification [34]. Based on the comparison, the one dimensional-CNN classifier has 90.93 percent of an average accuracy, because the ECG spectrograms as input without further manual preprocessing of the ECG signals.

Kanani and Padole introduced a redesigned DL topology that adds to the training stability with a pre-treatment strategy that considerably enhances the performance of DL techniques for ECG classification [35]. This study employed a preprocessing strategy that improved the accuracy of utilized DL models by 98 % without overfitting the model. Kulkarni and Dushyanth described a unique DL method that used Photoplethysmography (PPG) data to identify five heart beat label of arrhythmias. Two tasks were performed using the DL approach provided in this study. Poor signal quality was the primary cause of inaccuracy in arrhythmia detection utilizing PPG signals [37]. Due to its design, the design outperforms previous Arrhythmia detection algorithms and continues to perform well regardless of the changing distributions in the training and testing datasets. Li et al. demonstrated a customized CNN for heartbeat classification system, where multi-spatial deep characteristics of the cardiac cycle are retrieved by the recurrent convolutional layers of each channel with kernels of various receptive fields. A clinical device that uses this technique is expected to be very useful because it has a high classification accuracy of 99 percent and can detect abnormal heartbeats. The communication attentiveness module strategically highlighted informative aspects that helped identify different areas of the heartbeat [38].

Mathunjwa utilized 1D ECG data to uncover arrhythmias features for CNN classification that used spatial features and thus well suited for image analysis. To get better outcomes, sample measurement ECG segments were recorded, then two-stage classifications and R-peak recognition were employed [44]. As a result of this research, doctors now have a sophisticated way to identify and distinguish among heart beat label of arrhythmias with accuracies of 95.3 % ± 1.27 % for Database of MIT-BIH Atrial Fibrillation (MBAF) and 98.41 % ± 0.11 % for Database of MIT-BIH Malignant Ventricular Ectopy (MBMVE). Pandey and Janghela (2021) used a non-linear compressed component based a novel deep convolutional encoded feature (CEF), whereas BLSTM networks used for classification. These decoded features were provided as the BLSTM network analyzer as output [48]. Data from the BLSTM network revealed high accuracy with 99.52 percent and a processing speed of only 6.043 seconds. DL poses the excellent potential for classifying heartbeats from an ECG.

Ramesh et al. presented a unique strategy based on fusing several features taken from signals using various approaches and CNN. The multiple advantages included the morphological features extracted and principal component analysis. Every

ECG signal was first preprocessed to eliminate the backdrop, then segmented using a straightforward technique [49]. For reduce the features of morphological size, the Principal Component Analysis (PCA) was employed. Based on simulations using the database of MIT-BIH benchmark (MBB), this system has an average classification accuracy of 98 percent. As compared with basic approaches, the enhancement was approximately 5%. Romdhane and Pr described a deep neural technique based on a CNN model. Background subtraction may be fully automated and in combination with the classification phase by CNN models [50]. The utilized model attains high accuracy value 98.41 %, 98.38 % F1-score, 98.37 % precision, and 98.41 % recall, and thus this method outperformed other methods. Sannino and De Pietro presented DNN, a DL technique for ECG heartbeat classification [51]. This model proved to be more accurate and competitive in terms of sensitivity and specificity than the current state of the art. A huge amount of ECG data must also be automatically analyzed to detect abnormal heartbeats, which is a crucial effort.

Sellami and Hwang utilized a unique deep CNN for reliable heart segmentation based on basic DL algorithms. To solve the mismatch among classes, a nonlinear function was implemented to quantify the loss properly [52]. Despite using only one lead's ECG signal and no preprocessing, this method consistently outperforms traditional 5-class heartbeat detection methods. Finally achieved accuracy of 99.48%, 98.3% positive productivity, sensitivity of 96.67%, and 99.87% specificity for the intra-patient paradigm. For the the interpatient paradigm attains 88.34% accuracy, positive productivity of 48.25%, 90.90% sensitivity, and specificity of 88.51%. Su et al. employed STM32 that integrated with Internet-of-Things devices for equipment systems and data collecting, including a manometers cuff, thermometer, and pressure sensor. This as the central Internet-of-Medical-Things controller created a valvular cardiovascular disease testing system that uses a deep CNN to construct fitting predictions and analyze data [54]. With this valvular heart disease screening method, it was possible to identify valvular heart disease based on assessment of the distinctive signals of patients.

Ullah et al. utilized a model to classify tachycardia using DL models available to the public database [55]. This CNN model achieved 99.12 % accuracy rate, whereas CNN+LSTM model attains 99.3 % accuracy rate, and finally 99.29 % accuracy rate attained for the CNN + LSTM + Attention Model. However, the need to create wearables with integrated low-power consumption wearables is more critical. Vincent Paul et al. presented a learned in the classroom diagnostic system to forecast cardiovascular problems in 2021 [56] based on Back Proportion Neural Network (BP-NN). The efficient feature extraction is proceeded by mRmR. When compared to the BP-NN classifier without a feature selection method, the utilized model attained high accuracy rate and outperformed the other techniques. This classifier model achieved a high sensitivity of 98.21 %, high specificity of 97.85 %, the high precision value of98.41 %, high recall value of97.43 %, and accuracy of 97.09 %.

An end-to-end method was utilized by Xu et al. that used a deep CNN for extracting features using aligned heart function. This approach eliminated the necessity for hand-crafting elements and resulted in an optimal ECG representation of cardiac classification [59]. This classifier's sensitivity and specificity were greater than those produced by basic classifiers over a vast range of operational points. This classifier could match the performance of patient-specific classifiers while simultaneously benefiting patient autonomy. A novel effective and quick 1D-CNN model was developed by Yldrm et al. [61] that has advantage of non-complex structure that is all in one model such as feature extraction then selection and classification used in cloud based mobile computing. Deep one dimensional-CNN achieved 91.33% of recognition accuracy of 91.33 % and a classification time of 0.015 seconds for 17 cardiac arrhythmia diseases that are class labels.

Inference: This section discusses the details and results of DL-based algorithms for detecting heartbeats and heart diseases. In spite of this, both commercial and research solutions for the aforementioned approaches are computationally efficient, but neither is exceptionally resilient nor are they highly sensitive to hand-tuning parameters, which results in poor generalizability. For this purpose, researchers present a DL-based hybrid technique that is computationally lightweight but robust.

2.2. Hybrid Deep Learning-Based Heartbeat Detection Methods

Chen et al. utilized a system for classifying six heart beat label of arrhythmias information. In this work, the researchers employed a CNN and an LSTM network. The convolution layer combined the phases of extraction of features, image segmentation, and classification [27]. The recommended approach attained a mean accuracy of 97.15 percent for appropriate dataset. Though the proposed method attained good classification rate, because of the ECG signal's low amplitude, and non-linearity, appearing a rapid and accurate classification was challenging and intend to computational complexity. Huang et al. presented an appropriate classification approach based clever ECG classifier employing rapid compressed residual CNN for smart identification of arrhythmias and high accuracy (FCResNet where sub-signal samples dimensions of ECG is generated using the maximum overlap discrete wavelet transformation (MOWPT) that saving the execution time [33]. The average accuracy was 98.79 %, which can help to solve issues like low computing efficiency, difficult convergence, and model deterioration.

ECG heartbeats were classified for arrhythmia identification by Khatibi & Rabinezhadsadatmahaleh using DL and K-NNs that offer a unique feature learning technique. Varying classifications, such as decision trees, SVMs with Gaussian kernel, and regression trees, were used to classify the properties retrieved by this model [36]. Through the experimental results this method can obtain an average accuracy of 99.77 %, 99.99 % of high AUC, high precision value 99.75 %, and High recall value of99.30 % for heartbeat classification. Compared to typical machine learning models, this technique has a short computing time and good accuracy. Li et al. presented a BiLSTM-Attention based neural network that incorporating global sequential features from pulse activity to increase heartbeat generalization ability. The continuous-discrete wavelet approach was used to reduce the noise first. Secondly, the tagging database detects the R wave's peak, after which the P-QRS-T wave shape and RR interval were retrieved [39]. The recommended approach for this scheme has a total accuracy of 99.49 %. Because the BiLSTM-Attention model, when paired with the global sequence elements of cardiac activity, provides greater interpretability than previous techniques. However, this approach needs considerable ECG data to obtain improved accuracy.

Li et al. developed a novel method for classifying heartbeat named as S-shaped reconstruction approach using a two-dimensional with nineteen-layer deep squeeze-and-excitation residual network (SE-ResNet) [40]. The outcome results show that the SE-ResNEt attained effective accuracy value of 99.61%, positive prediction rate of 93.87 %, high sensitivity, and specificity of 93.78 %, and 99.27 % separately, because it extracting additional information from ECG heartbeat data. However, the algorithm's time complexity has substantially risen. Li et al. presented a DL algorithm for cardiac diseases identification based on the deep residual network (ResNet). A 31-layer one-dimensional residual CNN was established. Each of the hidden teams of 4 to construct identical shortcut interconnection that consists of three one dimensional convolution layers, batch normalization layers are 3 and linear activation layers of 3. Further, by combining 2-lead ECGs and DL, five different pulse rates [41] were detected manually with a sensitivity of 94.54 percent, an accuracy of 99.38 percent, and a specificity of 98.14 percent. Results obtained for single-lead ECG heartbeats were 99.6% accurate, 93.2% sensitivity, and 96.76 percent positive predictive value, respectively.

To classify the heartbeats of electrophysiology, Liu et al. developed three distinct autonomous classification methods. The approach was based primarily on a 1D CNN, and the best network structure was measured by examining the classification efficiency of several model specifications [42]. Stacking and SVM improve the CNN network. Based on the results, the stacking method has the most significant classification accuracy, with 99.1%. Lu et al. developed the LSTM networks with CNN network model was used for the arrhythmia classification approach, where deep CNN was anticipated to encode ECG signals and extract their morphological properties. Second, the fundamental data were mined thoroughly using the correlation coefficients of LSTM learning morphological representations. It was possible to classify arrhythmias automatically based on ECG features [43]. This approach dramatically reduced identification time and has a 96 percent accuracy rate with 91% of average positive retrieval rate and 92% of sensitivity.

Niu et al. developed a multi-perspective CNN (MPCNN) for cardiac segmentation in inter-patient ECGs [45]. This method attained high accuracy with 96.4 percent compared to other approaches. This technique could be customised to handle a variety of additional tasks related to ECG classification since it delivers effective heartbeat classification performance short of the requirement of sophisticated handmade features or the assistance of a human expert. Oh et al. presented an automated approach for diagnosing four regular normal heart rhythm on ECG data using a mix of CNN and LSTM [46]. The suggested approach achieved an accuracy of 98.10 %, sensitivity of 97.50 %, and specificity of 98.70 % with devoid of feature extraction, noise filtering and feature selection. Pal et al. reported a DL-based technique for heart disease identification from ECG. In proposed model, the weights were utilised to fine-tune CardioNet learning on the ECG dataset that was an autonomous system that used the idea of learning algorithms to classify heart function sooner and more reliably for arrhythmias diagnosis [47]. This CardioNet system outperformed existing approaches with a classification accuracy of 98.92.

Shi et al. suggested a CNN and LSTM network with several input layers for a unique automatic heartbeat classification system [53], which has the benefit of mixing automatically obtained data and hand-crafted features. For different inputs in CNN-LSTM model, various strides tested during the convolution process and thus resulting in accuracy of 99.26 percent for the class-oriented model and 94.20 percent and subject-oriented methods. For multi-class arrhythmia detection, Wang et al. suggested the Deep Multi-Scale Fusion deep convolution network (DMSFNet) structure. The ECG waveform can be efficiently captured and undesired noise can be reduced by using multiscale morphological procedures and cross-scale informational compatibility. This method combines numerous convolutional filters with different visual fields, resulting in automatic feature extraction. In two steps, a method that combines recurrence plot (RP) and transfer learning was utilized [57].

Xie et al. utilized feature enrichment (FE) with the classifier of CNN and named FE-CNN, improving the classification accuracy for heartbeat detection [58], which is simple to use, effective, and adaptable to many types of vital signs. Experiments using the Database of MIT-BIH Arrhythmia reveal that FE-CNN detected supraventricular ectopic (S) beats with a high sensitivity of 75.6 percent, 90.1 % of high positive predictive rate and effective F1 score of 0.82. For ventricular ectopic (V) beat identification, the results obtained 92.8 %, 94.5 %, and 0.94 for sensitivity, positive predictive rate and F1 score respectively. FE-CNN resulting in an F1 score of 0.75 to 0.82 for S beat identification, because this can work effectively without any hand-crafted features.

Yamamoto and Ohtsuki presented a pulse recognition approach that used convolutional LSTM (Bidirectional-Long Short-Term Memory) to correctly identify beats even at low heart rate using a Doppler monitor [60]. In this technique, sequential representations that could be attributable to the heartbeat were employed as an input to recreate a cardiovascular view that appears on the periodic beating and the spectrum pattern distinctive to overcome.

Inference: Some researchers have focused on this topic and provided a solution that CNN modelling has received a lot of recent attention. Features of heart beat dataset have been shown to increase efficiency of classification in experiments and thus the effective hybrid models can extract automatic features from heartbeat database. Creating an operative model for varied information has been the most apparent difficulty in CNN modelling. In creating a neural CNN, the construction of layer and model parameters is an important optimal challenge. Computations for ECG analysis should be constructed that is comparable to the effective models prepared on massive data. As a result, successful outcomes in this subject are likely to be attained using a transferring learning strategy. Deep neural networks perform well when executed on systems with vast volumes of high-quality data. As a result, researching newly developed massive ECG datasets might lead to more significant discoveries.

Table 2 describes the details of algorithms used in the literature part with the classes and performance metrics. Table 3 provides the advantages and disadvantages of the above-described algorithms.

3. PERFORMANCE ANALYSIS COMPARISON AND DISCUSSION

The four most often used models, such as Bi-LSTM, CNN, FCResNet, and ResNet, were assessed using the MB database's two-division schemes: class-oriented scheme and subject-oriented scheme. Every method's training set was used to train the model, while the test set was merely used to assess the model's ultimate performance. The validation set for HR detection was picked at random from the initial training set when such network was being trained. Correctness, sensitization, selectivity, accuracy, and F-Score performance objectives were used to assess the test data findings. The tests classified five unique classes, including sinus rhythm, APB, LBBB, RBBB, and PVC, using examples from the MIT - BIH Arrhythmia database. To recognize the heart, approaches such as Bi-LSTM, CNN, FCResNet, and ResNet are examined with the performance metrics such as Accuracy, Sensitivity, Specificity, Precision and F-Score as shown in (1-5). The numerical results are tabulated in Table 4. The formulas for five performance metrics are given in the Equation 1-5:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} * 100 \quad (1)$$

$$Sensitivity = \frac{TP}{TP+FN} * 100 \quad (2)$$

$$Specificity = \frac{TN}{TN+FP} * 100 \quad (3)$$

$$Precision = \frac{TP}{TP+F} * 100 \quad (4)$$

$$F1\ score = \frac{2*Precision*Recall}{Precision+Recall} \quad (5)$$

Where TP is the number of appropriately detected heartbeats, TN denotes the total number of appropriately undetected beats, FP denotes beats from other classes classified as this class, and FN denotes heartbeats classified as other classes.

3.1. Accuracy Comparison Results

The attained high accuracy is reviewed models for the number of features in a particular directory is shown in Fig.3. The ResNet improves accuracy while cutting down on production time. Because it does not require many derived components during reduction, the ResNet achieves 99.06 percent accuracy compared to all other algorithms. Consequently, this approach outperforms current techniques in improved validating findings for heartbeat prediction.

3.2. Sensitivity Comparison Results and Specificity Comparison Results

The sensitivity and specificity of reviewed models for the number of features in a specific are shown in Fig.4 and Fig.5. Both values are getting increased when the number of features is increased. The ResNet, for example, has a sensitivity of 93.21 percent and a specificity of 96.76 percent. The present CNN-based approaches are underfitting methods that are useless for high-dimensional datasets. Consequently, the ResNet-based system outperforms previous systems in improved testing findings for DR illness prediction. Because the ResNet system was fully unaffected by sudden feature shifts, it could be used to detect heartbeats.

3.3. Precision And F1 Score Comparison Results

The high precision value of reviewed models for the number of features in a specific directory is shown in Fig.6. Precision is increased when the number of features is increased. For example, ResNet has a high recall value of97.37 percent, CNN has a high recall value of98.41 percent, FCResNet has a high recall value of98.53 percent, and Bi-LSTM has a recollection of 99.2 percent. This is because the Bi-LSTM reduces the time it would take to compute the derived factors, allowing for easier Pattern recognition fine-tuning and therefore increasing the accuracy rate. The F1-sore of planned and current models for the number of features in supplied sources is shown in Fig.7. The f-measure is likewise maximised when the number of features is maximised. For example, the Convolution layer has an f-measure of 97.41%, whereas CNN seems to have an f-measure of 97.43 percent, FCResNet seems to have an f-measure of 94.7 percent, and Bi-LSTM has an f-measure of 98.6 percent.

3.4. Scientometric Analysis

Regarding the papers' published years, it's important to note that the search was restricted to the years 2015 to 2022, which was condensed as the year with the fewest submissions, as shown in Fig.8. The corresponding scientific facts may be determined based on the 60 papers analysed using heartbeat detection. Fig.9 shows that the Journal accounted for 30% of the publishing papers on Springer. 19% shows the journals refereed from other journals such as Biomedical Signal Processing and Control, Biomedical Engineering Letters, IRBM etc. 8% and 20% indicates the papers referred from the library of ACM and Elsevier. In comparison, involvement in seminars accounted for 23% of the articles, with IEEE-organized meetings distinguishing out nationally and worldwide.

Inference from the study: This study analyzed existing transfer learning studies on heartbeat ECG data. The following are some critical discoveries made due to these investigations: The ability to classify raw ECG signals using DL-based techniques without humans extracting the features is a significant benefit. However, several researchers have found that combining raw data with specific behavioural parameters (e.g. RR interval) enhances the performance of a model. The inconsistency of ECG datasets is an important concern and likewise have a lot of data comparative to others this determination lead for obtaining false information approximately system performance.

4. CONCLUSION AND FUTURE WORK

This research included a thorough examination and assessment of DL algorithms for tachycardia classification. DL for arrhythmia identification was investigated and addressed in peer-reviewed academic papers. An experimental investigation was provided to understand the approaches that make some serious learning useful for tachycardia detection. To test the effectiveness of the analyzed methods, researchers developed DL models to classify a five-class rhythm ECG dataset. The findings of several deep neural networks for heartbeat detection are provided here, along with answers to some of the field's most pressing issues. In future, research on the proper and effective clinical uses of models developed with DL models should be increased in subsequent analysis. It will be a significant incentive for DL algorithms to provide more effective future outcomes as public databases and data of specific classes grow in this direction. Moreover, due to the black-box structure of DL algorithms, what features are considered throughout the testing process remains an open subject. As a result, studying the factors that programs can consider for incoming information will be critical in producing increasingly trustworthy solutions. Traditional approaches have mostly focused on heartbeat detection in people with a normal heart rate greater than 50 beats per minute (bpm). Thus, a novel reliable heartbeat detection technology specifically for the people with low HR is required. Future studies will focus on hyperparameter tuning of the DL approach, which will increase the accuracy by adjusting the DL network topology to assure the real-time performance of the HR detection system.

5. DECLARATIONS

- Funding: Yes
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FIGURES AND TABLES

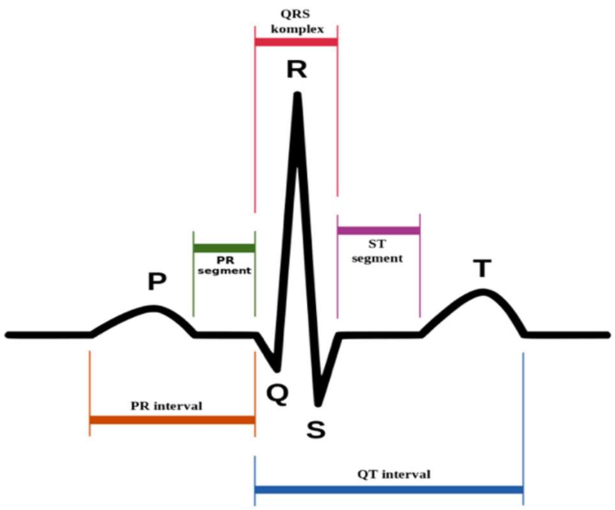

Fig. 1. *Heartbeat Cycle In An ECG [11]*

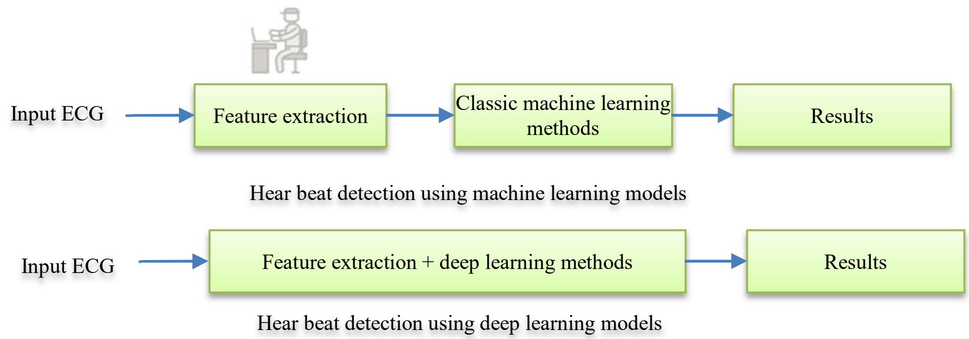

Fig. 2. *General Framework Of Comparative Illustration Of Deep Learning Framework And Machine Learning Framework*

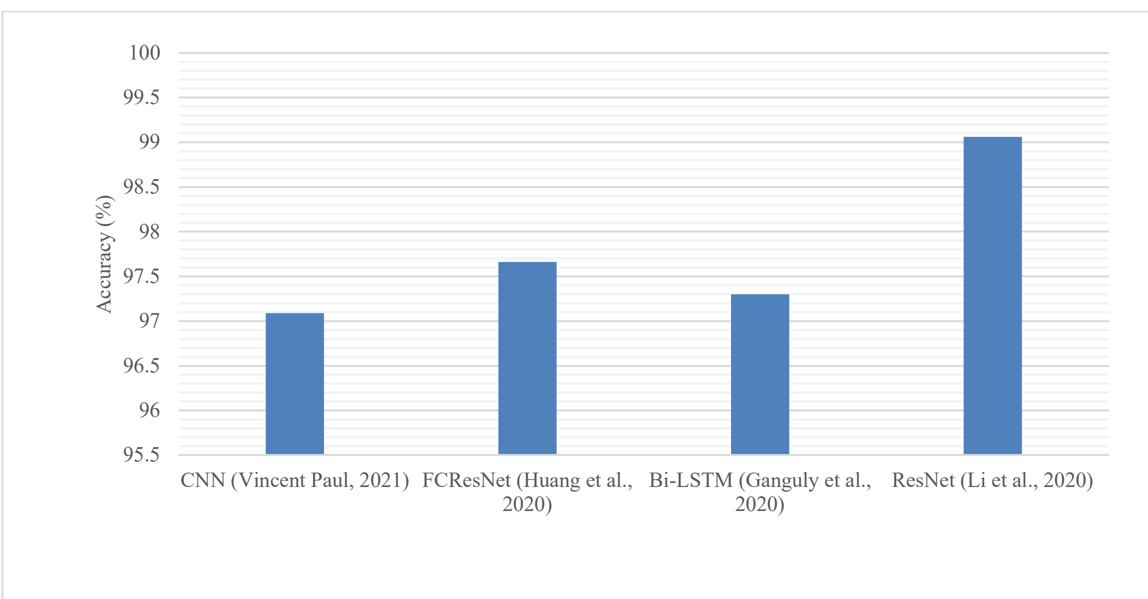

Fig. 3. *Accuracy Performance Comparison Results*

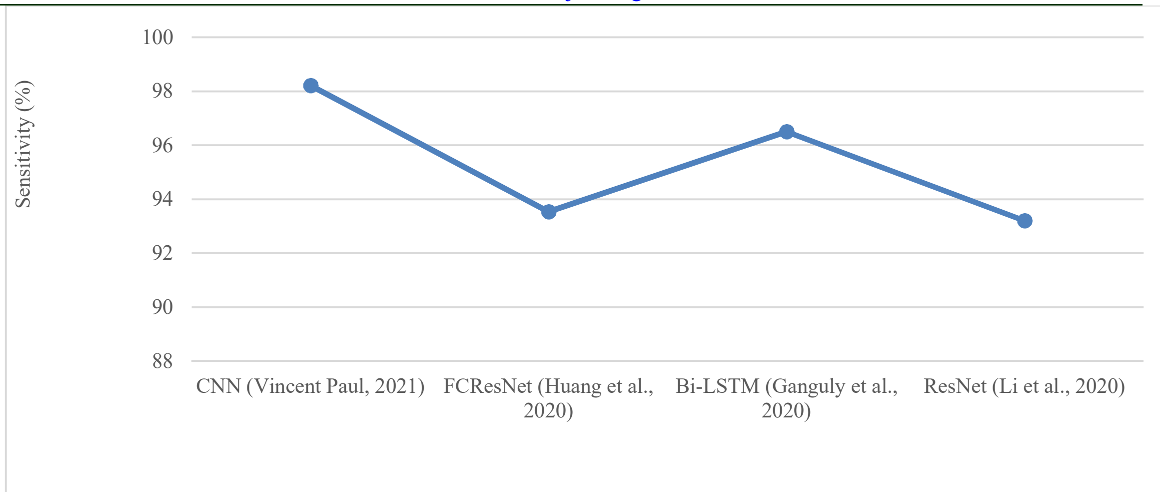

Fig. 4. *Sensitivity Performance Comparison Results*

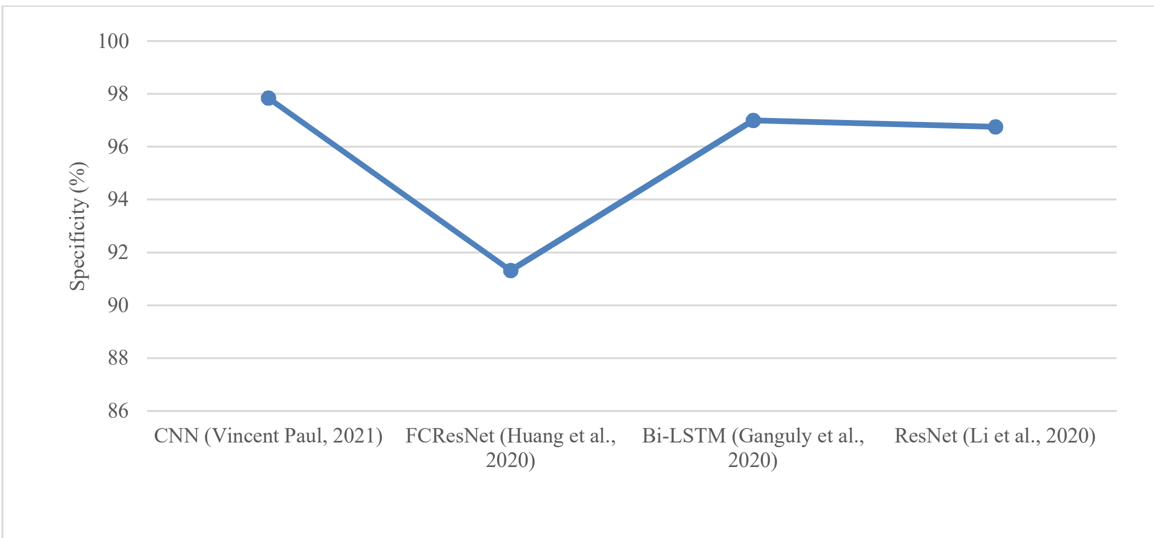

Fig. 5. *Specificity Performance Comparison Results*

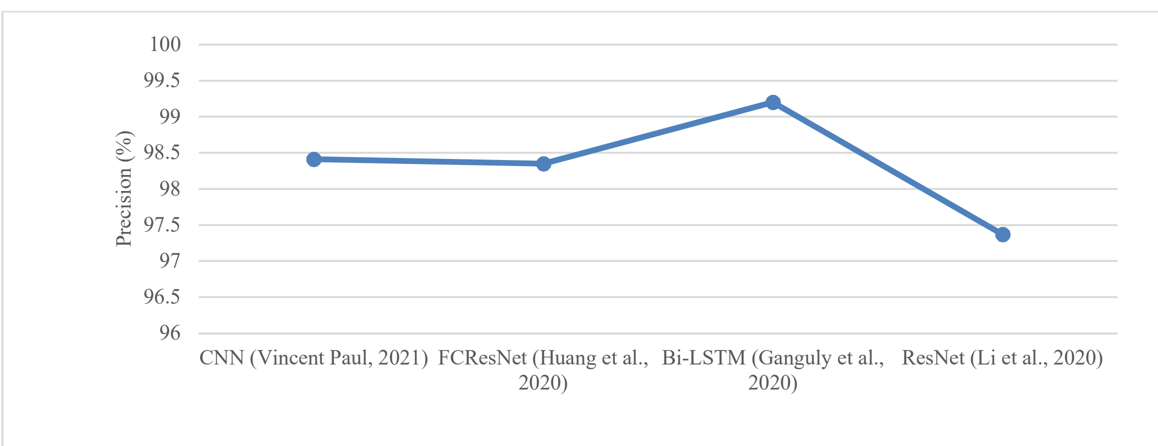

Fig. 6. *Precision Performance Comparison Results*

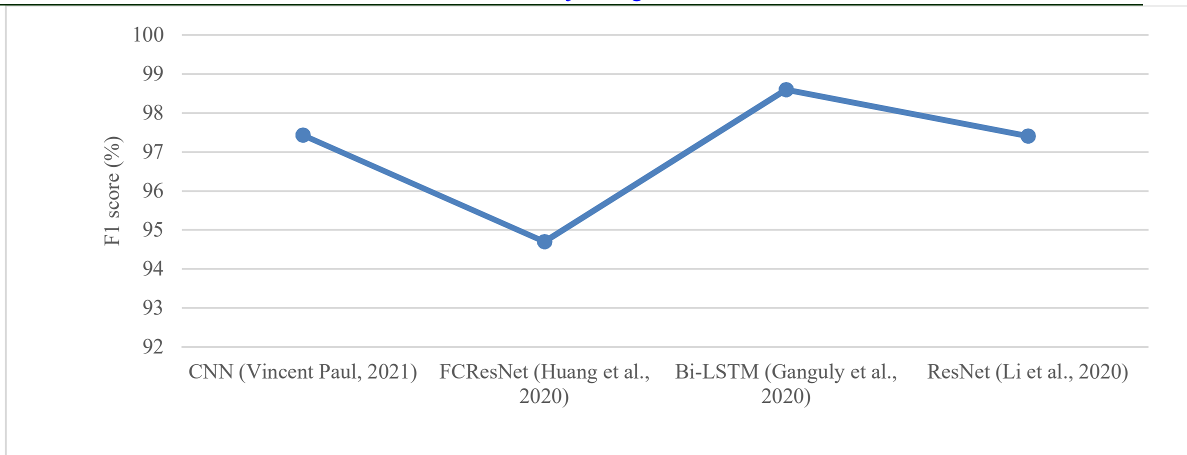

Fig. 7. *F1-Score Performance Of Comparison Results*

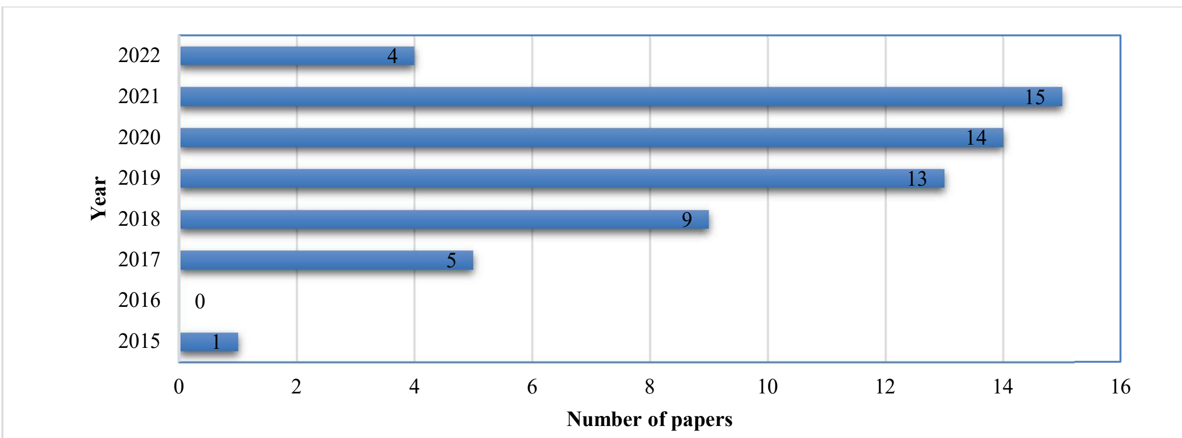

Fig. 8. *Analysis Of The Article According To The Year Of Publication*

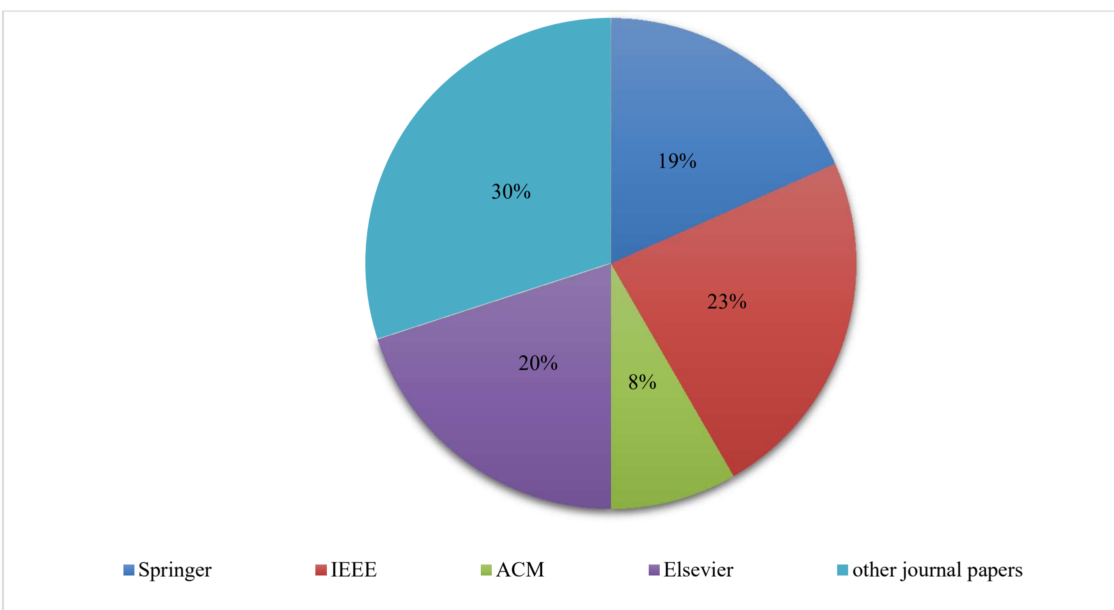

Fig. 9. *Origin Of The Publications By Various E-Library.*

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TABLE I. *DESCRIPTION OF THE ARRHYTHMIA DATASET [17]*

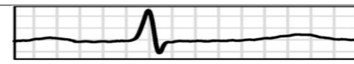
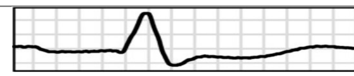
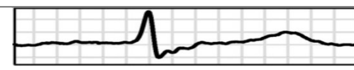
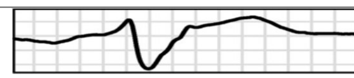
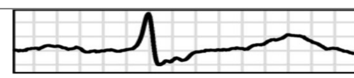
Type of Beats	Total number of Patients	Total number of Beats	Sample of waveform
Normal Beats (N)	47	75020	
Left Bundle Branch Block (LBBB)	47	8072	
Atrial Premature Beat (APB)	47	2546	
Premature Ventricular Contraction (PVC)	47	7129	
Right Bundle Branch Block (RBBB)	47	7255	

TABLE II. *Some Basic Studies Use Deep Learning Techniques On Ecg Signals*

Study	Database	Classes	DL method	Results
Alqudah & Alqudah (2022)	744 ECG signals for 45 persons	17	CNN	attained high accuracy is 99.13% ± 0.25, 98.223% ± 0.85, and 97.494% ± 1.26 for 13, 15, and 17 arrhythmia classes, respectively
Khatibi, T., & Rabinezhadsadatmahaleh (2020)	MIT-BIH datasets	4	CNN	average Attained high accuracy is 99.77%, High AUC with rate of 99.99%, High precision value of99.75% and High recall value of 99.30%
Acharya et al. (2019)	• Database of Beth Israel Deaconess Medical Centre (BIDMC) Congestive Heart Failure • Database of MIT-BIH Normal Sinus Rhythm (NSRDB) • Fantasia Database	4	11-layer deep CNN	attained high accuracy is 98.97%, high specificity and sensitivity of value of 99.01% and 98.87%
Deevi et al., (2021)	PhysioNet's MIT-BIH	10	HeartNetEC	High precision value of 98.42%, high recall value of 98.42%, F1 score 98.42% and accuracy 98.42%
Huang et al., (2020)	MIT-BIH	5	FCResNet	High precision value of 98.35 %, high recall value of 91.31 %, F1 score 94.70 % and accuracy 97.66%
Ramesh et al. (2021)	MIT-BIH benchmark database	15	CNN	attained high accuracy is 98.2500%
Lu et al. (2021)	Database of MIT-BIH Arrhythmia	13	CNN-LSTM	accuracy 96, positive retrieval rate 91% and sensitivity 92%

Dokur & Ölmez (2020)	Database of MIT-BIH Arrhythmia	11	CNN	average success rates of 99%
Pandey & Janghela (2021) Yamamoto and Ohtsuki (2020)	Database of MIT-BIH Arrhythmia	5	Bi-LSTM	attained high accuracy is 99.52% and processing time 6.043 s.
Abdalla et al. (2020)	Database of MIT-BIH Arrhythmia	10	CNN	99.84% accuracy
Vincent Paul (2021)	Database of MIT-BIH Arrhythmia	10	CNN	sensitivity 98.21%, specificity 97.85%, high precision value of 98.41%, high recall value of 97.43%, and 97.09% accuracy
Ahmad et al. (2021)	PhysioNet's MIT-BIH	5	CNN	accuracy 99.7%
Wang et al., (2020)	CPSC_2018 and PhysioNet/CinC_2017	4	DMSFNet	High precision of 0.838%, high recall of 0.822%, F1score0.828
Mathunjwa (2021)	• Database of MIT-BIH Arrhythmia • MIT-BIH Atrial Fibrillation Database • Creighton University Ventricular Tachyarrhythmia Database • MIT-BIH Malignant Ventricular Ectopy Database	6	CNN	accuracies up to 95.3 % ± 1.27 % and 98.41 % ± 0.11 %
Chen et al. (2020)	Database of MIT-BIH Arrhythmia	6	CNN-LSTM	attained high accuracy is 97.15 %
Xie et al., (2019)	Database of MIT-BIH Arrhythmia	5	FE-CNN	sensitivity 75.6%, positive predictive rate 90.1%, and F1 score 0.82%
Niu et al. (2019)	supraventricular ectopic beat (SVEB) and ventricular ectopic beat (VEB) on the MIT-BIH arrhythmia dataset	5	MPCNN	attained high accuracy is 96.4%, F1 scores for SVEB and VEB of 76.6% and 89.7%, respectively
Huang et al. (2019)	Database of MIT-BIH Arrhythmia	5	2D-CNN	attained high accuracy is 90.93%
Xu et al. (2018)	Database of MIT-BIH Arrhythmia	15	DNN	Overall accuracy 99.70% SEN of class PVC 97.68% SPC of class PVC 99.89%
Li et al. (2019)	Database of MIT-BIH Arrhythmia	5	CNN	accuracy and specificity of 99%, sensitivity of 95.4% and positive predictivity of 97.1%
Ganguly et al. (2020)	MIT-BIH arrhythmia dataset	5	Bi-LSTM	Accuracy 97.3%, 96.5%, sensitivity, high precision value of 99.2% and specificity 97.0% f1-score 98.6
Li et al. (2019)	Database of MIT-BIH Arrhythmia	5	BiLSTM-Attention neural network model	Accuracy 99.49%
Sannino & De Pietro (2018)	Database of MIT-BIH Arrhythmia	5	DNN	Attained high accuracy is 99.68%, sensitivity 99.48% and specificity 99.83%

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Kanani & Padole (2020)	Database of MIT-BIH Arrhythmia	5	CNN	Ranking based Average high precision value of 0.9912%, f1-score 0.98%, Weighted Ranking Loss 0.0047 and Coverage error 1.0190
Hu et al. (2022)	Database of MIT-BIH Arrhythmia and MIT-BIH atrial fibrillation database	8, 4 and 2	ECG DETR	overall attained high accuracy is 99.23%
Li et al. (2020)	single-lead ECG heartbeats and 2-lead datasets	5	ResNet	average accuracy, 99.06%, sensitivity and 93.21% and positive predictivity of 96.76%
Degirmenci et al. (2021)	(2D) ECG beat images	5	CNN	attained high accuracy is 99.7%, sensitivity of 99.7%, and specificity of 99.22%
Romdhane & Pr (2020)	MIT-BIH and INCART datasets	5	CNN	98.41% overall attained high accuracy is, 98.38% overall F1-score, 98.37% overall high precision value of, and 98.41% overall high recall value of.
Sellami & Hwang (2019)	ECG signal	5	DCNN	Attained high accuracy is 99.48%, positive productivity 98.83%, sensitivity 96.97% and specificity 99.87%
Pal et al. (2021)	MIT-BIH arrhythmia and PTB	29	CardioNet	Attained high accuracy is 98.92%
Shi et al. (2020)	Database of MIT-BIH Arrhythmia	5	CNN-LSTM	attained high accuracy is 99.26%
Acharya et al. (2017)	ECG Database	5	Deep CNN	attained high accuracy is 94.03%
Ullah et al. (2021)	Database of MIT-BIH Arrhythmia	5	CNN + LSTM + Attention Model	Attained high accuracy is 99.29%
Liu et al. (2019)	Database of MIT-BIH Arrhythmia	4	CNN	attained high accuracy is 99.1%
Yıldırım et al., (2018)	MIT - BIH Arrhythmia database	17	Deep 1D-CNN	Attained high accuracy is 91.33%
Oh et al. (2018)	MIT-BIT arrhythmia physio bank database	5	CNN-LSTM	attained high accuracy is 98.10%, sensitivity of 97.50% and specificity of 98.70%

TABLE III. *Comparative Study On DL Methods With Their Advantages And Disadvantages*

Method with Author	Advantages	Disadvantages
Convolutional Neural Network (CNN) (Alqudah & Alqudah (2022), Rabinezhadsadatmahaleh (2020), Acharya et al., (2019), Ramesh et al., (2021), Dokur & Ölmez (2020), Abdalla et al., (2020), Vincent Paul (2021), Ahmad et al., (2021), Mathunjwa (2021), Huang et al., (2019), Li et al., (2019), Kanani & Padole (2020),Degirmenci et al., (2021),Romdhane & Pr (2020),Liu et al., (2019))	Automatic feature extraction will improve the detection accuracy	Accepts small dataset and lead to overfitting problem, so the augmentation of the dataset is essential.
FCResNet (Huang et al., (2020))	Attains less computational Complexity for detection of the heartbeat	However, the number of hidden layers are extraordinary. Accuracy is low
CNN-LSTM (Lu et al., (2021), Chen et al., (2020), Shi et al., (2020), Oh et al., (2018))	This work attains a small amount of data resulting in better generalisation ability.	It does not execute well on high-dimensional data.
Bi-LSTM (Pandey & Janghela (2021), Ganguly et al., (2020), Li et al., (2019))	This method can learn complex features, and thus, the computational complexity is reduced.	However, they did not contemplate some preprocessing techniques and thus reduced the quality of the image, resulting
DMSFNet (Wang et al., (2020))	This work has preprocessing and handles a large dataset	Attains class imbalance problem
CNN-LSTM (Chen et al., (2020))	Use extensive data and prolonged training times are not necessary	The quality of the images could be insufficient.
FE-CNN (Xie et al., (2019))	It necessitates much less preprocessing	It is challenging to achieve good performance with a limited number of images.
MPCNN (Niu et al., (2019))	It is unaffected by image noise and thus improves the accuracy	Still, a large number of images are needed to train MPCNN
DNN (Sannino & De Pietro (2018))	Learning complex patterns also reduce computation time	Consumes a lot of processing power for training
CNN + LSTM + Attention Model (Shi et al., (2020), Ullah et al., (2021))	The method is simple and can be applied in different imaging	There is a possibility of data loss

TABLE IV. *Experimental Results Of DL Methods*

Methods	Accuracy	Sensitivity	Specificity	Precision	F-Score
CNN (Vincent Paul, 2021)	97.09	98.21	97.85	98.41	97.43
FCResNet (Huang et al., 2020)	97.66	93.54	91.31	98.35	94.70
Bi-LSTM (Ganguly et al., 2020)	97.3	96.5	97.0	99.2	98.6
ResNet (Li et al., 2020)	99.06	93.21	96.76	97.37	97.41