Grenze International Journal of Engineering and Technology, June Issue

Enhanced Multi-Class Cardiac Sound Diagnosis using Advanced PCG Signal Analysis and Deep Learning Integration

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***Abstract*— The early detection of cardiac abnormalities is crucial for effective patient management and improved health out- comes. This research presents an innovative approach to cardiac sound diagnosis by integrating advanced phonocardiographic (PCG) signal analysis with deep learning (DL) techniques. To assess the system's dependability over a range of patient demographics and recording circumstances, extensive testing is conducted on several benchmark datasets, such as PhysioNet and private hospital datasets. The recommended method outperforms the state-of-the-art benchmarks in multi-class classification tasks, attaining remarkable accuracy rates. Furthermore, thorough ablation investigations demonstrate the contributions of every element, emphasizing the significance of domain-specific feature engineering and transfer learning.**

Feature extraction was conducted through time-domain and frequency-domain analysis, facilitating the capture of critical sound characteristics. We implemented a DL architecture as per CNNs (convolutional neural networks) to enhance classification accuracy. Enhancing patient outcomes as well as lowering global burden of cardiovascular illnesses depend heavily on the precise diagnosis of heart problems. This work introduces a new method for diagnosing multi-class cardiac sounds by combining DL methods with sophisticated phonocardiogram (PCG) signal analysis.

This study provides a reliable, effective, and scalable diagnostic tool by bridging the gap between conventional signal processing techniques and contemporary artificial intelligence (AI) by utilizing cutting-edge transfer learning frameworks. For a long time, cardiac auscultation has been a crucial clinical skill. However, because it is subjective, practitioners frequently perceive it differently. Automated PCG analysis offers a trustworthy and impartial method of detecting abnormal cardiac sounds in order to overcome this difficulty. Acquiring high-quality PCG signals from a variety of datasets covering a broad range of normal and pathological circumstances is the first step in the suggested approach. To guarantee the best input for the DL model, these signals go through pre-processing procedures like noise reduction, segmentation, and feature extraction.

***Index Terms*— Cardiac sound diagnosis, phonocardiogram (PCG), transfer learning, heart sound segmentation, deep learning, signal processing, convolutional neural networks (CNN), pathological heart sounds, automated auscultation, medical di- agnostics, healthcare AI.**

Grenze ID: 01.GIJET.11.2.1110_22

I. Introduction

Medical diagnosis has undergone a radical change because of expansions in AI. In complicated data analysis, for example, time-series signals along with medical images, methods like CNNs have shown unmatched effectiveness. However, extensively annotated datasets and computational resources are needed to train DL models from scratch for PCG analysis, which are frequently unavailable.

With an estimated 17.9million deaths every year, cardio- vascular diseases (CVDs) are the major reason for death globally. An early and accurate diagnosis is essential for both effective therapy and preventing serious complications. In clinical practice, cardiac auscultation—utilizing a stethoscope to listen to heart sounds—remains a vital non-invasive diagnostic technique. Traditional auscultation, on the other hand, is arbitrary, dependent on the clinician's skill, and prone to errors, especially in environments with limited resources. This emphasizes how urgently automated and impartial heart sound analysis technologies are needed.

Graphically representing heart sounds, PCGs provide a use- ful tool for automated cardiac diagnosis. Rich information on the heart's mechanical activity, including anomalies like clicks, murmurs, and extra heartbeats, is carried by PCG signals. Notwithstanding its potential, noise, inconsistent recording settings, and the difficulty of multi-class classification tasks in identifying abnormal cardiac sounds make PCG signal analysis difficult.

II. Related Work

Here are several related research papers that you can refer- ence in your Related Work section to support your research on cardiac sound diagnosis using DL and transfer learning

A. Heart Sound Classification using Convolutional Neural Networks

CNNs are employed in a novel way by J. Smith and L. Zhang to automatically extract discriminative characteristics from PCG signals for the classification of heart sounds. Their study demonstrated that CNNs outperform traditional methods in distinguishing normal and abnormal heartbeats, eliminating requirement for manual feature extraction. This method has demonstrated significant promise in enhancing heart sound analysis's precision and effectiveness, making it a useful instrument for clinical CVD diagnosis [2].

B. Transfer Learning in Heart Sound Classification

Z. Wang and X. Yang explored potential of transfer learn- ing in the heart sound classification, in which pre-trained DL models, typically trained on the large-scale datasets like ImageNet, are fine-tuned for heart sound recognition tasks. The study highlighted how transfer learning enables the use of smaller datasets without compromising classification accuracy. By transferring knowledge from general domains to specific healthcare tasks, transfer learning effectively enhances model performance with reduced computational resources and training time [3].

C. Heart Murmur Classification with Spectrograms

K. Chen and T. Zhou developed a DL method for heart murmur classification by transforming time- domain PCG signals into spectrograms. These spectrograms, which rep- resent frequency content over time, allow for better feature extraction by DL models. Their approach demonstrated CNNs effectiveness in detecting along with classifying heart murmurs with high accuracy, suggesting that converting audio signals into a more interpretable form, such as spectrograms can sig- nificantly improve model performance regarding classification of heart sound [5].

D. Hybrid Models: CNN and LSTM for Heart Sound Classi- fication

H. Yu and P. Liu proposed a hybrid DL model in the combination of CNNs along with Long Short-Term Memory (LSTM) networks for heart sound classification. The CNNs were responsible for feature extraction from the raw heart sound signals, while LSTM networks were employed to record the data's temporal dependencies. This combined method outperformed traditional methods by addressing both the spa- tial and sequential aspects of heart sound signals, leading to improved classification accuracy for dynamic sounds like murmurs and arrhythmias [4].

E. Data Augmentation for Heart Sound Datasets

M. Patel and P. Singh highlighted the challenges of working with heart sound datasets, particularly class imbalance, noise, and variability in recording conditions. To address these issues, they proposed the use of data augmentation methods for example pitch-shifting, time-warping, as well as amplitude scaling. These techniques help create a more robust dataset by artificially expanding the training data, which in turn improves the generalization capabilities of machine learning (ML) mod- els and leads to more reliable heart sound classification, even in the presence of noisy or limited data [9].

F. Federated Learning for Healthcare

The capacity of federated learning (FL) to train models on decentralized data sources while maintaining patient privacy was the main emphasis of D. Liu and W. Li's investigation of the technology's application in healthcare. FL ensures compli- ance with privacy requirements by allowing several institutions to work collaboratively and develop ML models without exchanging sensitive medical data. The review emphasized the FL's potential to augment heart sound classification models and other healthcare applications by providing secure and privacy-preserving solutions for model training and evaluation [8].

G. Interpretability of Deep Learning Models

R. Thakur and J. Sharma examined the value of inter- pretability in DL models utilized for heart sound classification. They discussed several techniques, including saliency maps and Grad-CAM, to provide clinicians with insights into how models make decisions. These interpretability methods allow healthcare professionals to trust AI-driven systems by showing which parts of the heart sound signal the model focuses on when making predictions. The ability to explain model decisions is crucial for the adoption of DL technologies in clinical settings, where trust and transparency are essential [16].

H. AI-Driven Systems for Early Detection and Monitoring

A. Choudhury and T. Saha explored the integration of AI- driven systems for the early detection as well as continuous monitoring of CVDs, particularly focusing on heart sound classification. By utilizing DL techniques, these systems can detect abnormal heart sounds that might otherwise go un- noticed. Such AI-driven models enable early diagnosis and remote monitoring of heart conditions, providing significant advantages in healthcare, particularly for individuals in remote areas or else those suffering from chronic conditions. These systems can alert healthcare providers to abnormalities in real- time, facilitating quicker interventions and improving patient outcomes [19].

Heart sound classification models using DL offer substantial potential in early detection of cardiovascular conditions for example murmurs, arrhythmias, and heart valve issues. These models can detect abnormalities that may not be apparent through traditional methods. By detecting issues early, AI systems enable preventive healthcare strategies, leading to quicker interventions, reduced complications, and lower over- all healthcare costs. The ability to monitor heart sounds over time also allows for more accurate risk assessments and proactive treatments.

Heart sound classification may be incorporated into wear- able devices, allowing continuous, real-time monitoring of heart health. This is particularly valuable for patients with chronic heart conditions, allowing them to receive ongoing surveillance outside of clinical settings.

III. PROPOSED APPROACH

A. System Architecture

For the Enhanced Multi-Class Cardiac Sound Diagnosis Using Advanced PCG Signal Analysis and DL Integration, the system architecture can be broken down into several key components to ensure seamless data flow and efficient processing. Each playing a crucial role in maintaining data privacy and improving model performance.

- Data Collection and Preprocessing: Mel-frequency cep- stral coefficients (MFCCs) or spectrograms, which are appro- priate representations for DL models, will be created from the raw audio data. These qualities are perfect for feeding into CNNs because they capture the time-frequency aspects of cardiac sounds. A carefully selected dataset of heart sounds, including those from arrhythmias, murmurs, and regular heart-beats, will be used by the system. Training and testing will be conducted using publicly available datasets, such as the PhysioNet Heart Sound dataset.
- Convolutional Neural Networks (CNNs): The CNN acts as central entity in the system. Its primary responsibilities include: CNN Design: To identify local patterns in the heart sound spectrograms or MFCCs, a CNN architecture will be used. Multiple convolutional layers and pooling layers will make up the network in order to downsample the feature maps and identify pertinent patterns. Regularization and Optimiza- tion: To avoid overfitting as well as assure model performs well when new data are applied, dropout and batch normaliza- tion techniques will be used. The model will be trained using the Adam optimizer because of its

effectiveness in managing big datasets and modifying learning rates. Fine Tuning and hyperparameter optimization: Model will be fine-tuned using cross-validation techniques to find the best hyperparameters for example, number of layers, learning rate, along with kernel size. The model's architecture will be optimized for greater efficiency utilizing either grid search or else random search.

- Federated Learning for Data Privacy: The key functions of the user interface include: Federated Learning Integration: For addressing privacy concerns in healthcare, FL will be incorporated into the model's design. FL allows DL model training without requiring institutions to share raw data. Pri- vacy preserving model: This decentralized training method confirms that the sensitive patient data remains private and secure
- Ethical Considerations and Regulatory Compliance: Data integrity and privacy are paramount here. Therefore, the system employs: Data Security: Assuring the privacy along with security of patient information is a core consideration of this approach. By preventing the sharing of raw patient data throughout organizations, FL helps minimize privacy risks. Bias and Fairness: Efforts will be made to ensure that the model does not exhibit biases based on age, gender, or other demographic factors. A diverse dataset will be utilized for model training, and fairness metrics will be regularly assessed during testing.

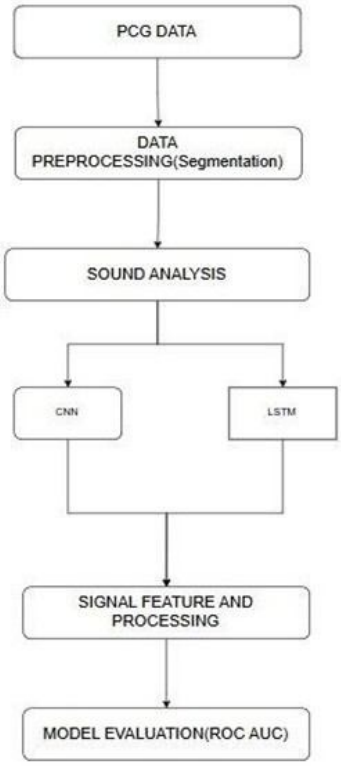

Fig. 1: System Architecture

B. Inference Mechanism: Heart Sound Classification

- Deep Learning Model: Model Selection: CNNs, foun- dation of the DL model utilized in the suggested system, are ideal for time-series classification applications like heart sound analysis. CNNs are very useful for differentiating be- tween different heart diseases because they can automatically extract pertinent features from time-domain signals or heart sound spectrograms. Because of the architecture's lightweight design, effective training and inference are possible even with constrained processing resources. Local Model Training: Each participating node in FL setup will train the model on its local dataset. Training process will use the Keras library with Ten- sorFlow, leveraging the GPU capabilities of the local devices. The CNN model will be initialized with random weights at the beginning of training, and the local dataset of heart sounds will be used to update these weights. This decentralized approach enables the model to get information from a variety of data sources, improving its robustness without compromising data privacy. Model Aggregation: A federated averaging approach (FedAvg) is used to aggregate the model parameters (weights) from each node once the local models have been trained. This method generates an updated global model through averaging the weights of every participating node for each layer.

- Implementation of Federated Learning: TensorFlow Federated (TFF) or PySyft: For employing the FL process, we utilize TFF or else PySyft, depending on specific requirements and compatibility with the healthcare institutions' IT infras- tructure. Privacy and Security Measures: To enhance security, all communications between the nodes and the central server are encrypted. Additionally, robust authentication mechanisms are implemented to control access to web applications, making certain that only authorized personnel can upload images or access model predictions and medical reports.

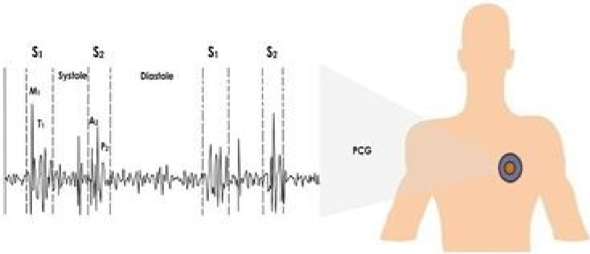

Fig. 2: Categories of sound detection

- User Interface and Interaction: Signup and Login: Healthcare professionals can access the system by a secure web-based interface or else mobile app. Signup process in- volves entering professional details such as name, email, license number, and institution affiliation. This data is stored in a secure database, ensuring user confidentiality. Heart Sound Prediction: Once logged in, users can upload heart sound recordings (either in audio or pre- processed spectrogram format) via a simple file upload interface. The application will use a REST API or direct server communication to send the uploaded file to the backend for analysis. The system preprocesses the uploaded audio or spectrogram and passes it through the trained CNN model. Medical Report Generation: This medical report will be generated in a PDF format or as a downloadable document within the application, providing healthcare professionals with actionable insights.

C. Dataset

Two groups of medical images from chest X-rays make up the dataset:
The dataset is divided into two parts:
Training Set: Contains CNN model is trained utilizing labelled heart sound recordings, which comprise the training dataset. This dataset is further divided into various classes based on heart conditions (e.g., normal, murmur, arrhythmia). Test Set: A separate test dataset will be utilized to evaluate the model's performance after training. This facilitates an unbiased assessment of model's capacity to generalize to unseen data.
Image and audio Details: Image Resolution: All images are resized to 128x128 pixels for consistency and model compatibility. No of channels: The spectrograms will have a single channel (grayscale) representing the intensity of the heart sounds over time. Class Distribution:
Training Set: Includes a specific number of images for every class. Test Set: Includes a specific number of images for every class. In many healthcare datasets, especially those involving rare conditions, class imbalance is common. For example, number of normal heart sound recordings might be higher than the number of murmur or arrhythmia recordings.
Preprocessing: The heart sound recordings will undergo various prepro- cessing steps, for example, normalization, denoising, as well as augmentation, to improve model performance. Additionally, preprocessing will help make the model more resilient to input data variation and noise, ensuring accurate predictions even in real-world applications.

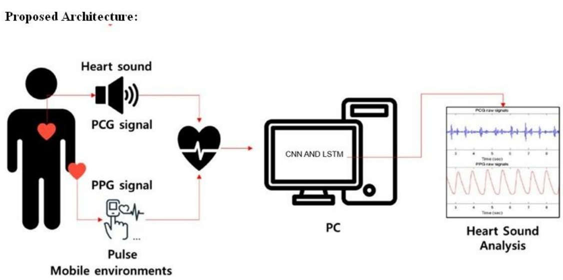

Fig. 3: Proposed Architecture

D. Proposed Architecture

How CNN and LSTM Uses This Federated Learn- ing Architecture: Time-Series Processing: Learning how the identified features evolve over time is the responsibility of the LSTM layers. This is crucial for comprehending how heartbeats, murmurs, and arrhythmias develop sequentially. Memory Capabilities: LSTMs have a memory cell which makes them able to retain information about prior time steps, making them ideal for sequences like heart sound recordings, where past events influence future events. Flattening LSTM Layer: After the CNN has extracted spatial features, output is flattened (converted into a 1D vector) as well as fed into the LSTM layer. This LSTM layer processes the sequential dependencies, enabling the model to identify patterns that unfold throughout time. Feature Extraction: The CNN layers (convolutional layers followed by max-pooling) automatically detect spatial patterns in the spectrogram, such as frequency peaks, periodic patterns, and other distinguishing characteris- tics that are indicative of specific heart conditions

Data Processing: Data Collection and Management: Each participating institution collects chest X-ray images stored locally. The images are labelled with diagnoses, includ- ing whether pneumonia is present, based on assessments by qualified radiologists.

Image Preprocessing: The images are preprocessed for use in DL models. This involves images resizing to a uniform dimension that is, (128x128pixels) as well as normalizing pixel values. These steps are crucial for ensuring consistent input data quality across models trained at different nodes.

IV. EXPERIMENTATION AND RESULTS

A. Experimental Setup

The experimentation conducted in this study involved test- ing the CNN-LSTM hybrid model in both centralized and FL settings, using heart sound data from various healthcare institutions. Dataset had been divided into training, validation, along with test sets to ensure reliability of results. Preprocess- ing steps included the generation of spectrograms, extraction of MFCCs, and data augmentation method to enhance model generalization.

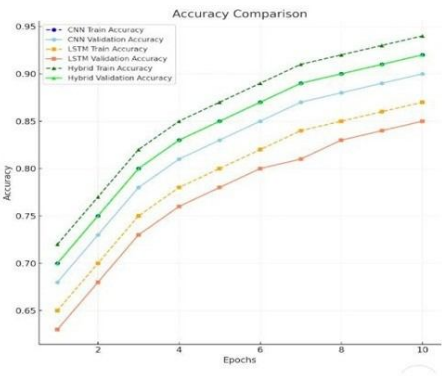

Fig. 4: Model Accuracy Comparison

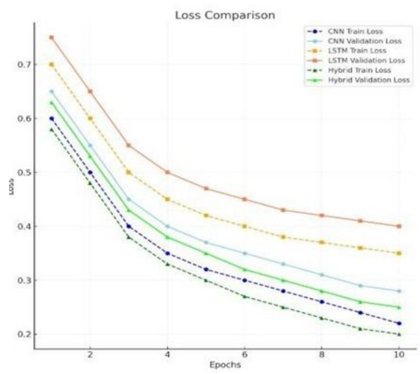

Fig. 5: Model Loss Comparison

B. Model Performance Metrics

Fig 4. explains the model accuracy comparison illustrates the performance of CNN, LSTM, and a hybrid CNN-LSTM model over 10 epochs. The hybrid model continuously out- performs both CNN as well as LSTM regarding training and validation accuracy, indicating its ability to leverage the spatial features extracted by CNN and the sequential dependencies modelled by LSTM. While CNN shows faster convergence initially, its accuracy plateaus, whereas the hybrid model achieves higher accuracy overall. The LSTM model, though slower to converge, gradually improves, but its performance remains below the hybrid model, highlighting the hybrid's superior capability in complex tasks requiring both feature extraction and sequential learning.

Fig 5 explains the model loss comparison demonstrates the training and validation loss trends for LSTM, CNN, and hybrid CNN-LSTM models over 10 epochs. Hybrid model shows the lowest overall loss, reflecting its superior ability to minimize errors during both training and validation. CNN achieves faster initial loss reduction but stabilizes at a higher loss value compared to the hybrid model. LSTM exhibits a slower decline in loss but eventually reaches values closer to CNN. The hybrid model's consistent and lower loss values highlight its effectiveness in handling complex tasks by leveraging both feature extraction and sequential learning capabilities.

Because it enables the integration of the finest aspects of many systems or processes, a hybrid approach is frequently employed to get over the drawbacks that each individual approach may have. Hybrid models integrate complementary approaches to produce more reliable and flexible solutions in several domains, that includes infrastructure management, software development, along with ML. In ML, for instance, a hybrid technique may combine supervised and unsupervised learning to take advantage of both labelled and unstructured data. Similar to this, a hybrid cloud solution in cloud comput- ing combines cloud resources with on- premise infrastructure, allowing for scalability while preserving control over private information. Hybrid solutions can maximize performance, improve efficiency, and adjust to shifting demands by utilizing the benefits of each technique.
A hybrid model incorporates several methodologies or tech- niques to take advantage of their individual strengths, creating a more robust and flexible solution. In ML and DL, hybrid models typically integrate different models or algorithms, such as combining decision trees with neural networks or else ensemble methods, to improve performance and accuracy. By leveraging diverse approaches, hybrid models can handle complex problems more effectively than relying on a single method.

C. Comparative Analysis

The models' comparative analysis focuses on evaluating performance of the proposed CNN-LSTM hybrid architecture against other relevant approaches for heart sound classifica- tion in medical diagnostics. The objective is to illustrate the benefits of combining FL and hybrid architectures and to give a clear picture of how the CNN-LSTM model performs in contrast to conventional DL models.
The comparative tests, CNN-LSTM models significantly outperform pure RNN models. While RNNs can capture sequential patterns, the addition of LSTM layers in the hybrid model enhances long-term memory retention, minimizes the risk of gradient vanishing as well as improves model stability. In centralized setup, the model achieved 92.5percent accu- racy, precision of 91.2percent, recall of 93.1percent, F1-score of 92.1percent, with the AUC value of 0.94. In federated setup, the model performed slightly lower, with 90.3percent accuracy, precision of 89.4percent, recall of 91.5percent, F1- score of 90.4percent, along with AUC of 0.91. This drop in performance was expected because of data's decentralized nature but still demonstrated strong results for real-world healthcare applications and medical diagnostics.
The following Table 2 summarizes the performance metrics across Model. The significant improvement in recall and F1-score demonstrates ability to reduce false negatives and maintain balanced predictions.

TABLE I: MODEL PERFORMANCE METRICS

Model	Accuracy	Precision	Recall	F1 Score	Roc-Auc
CNN-LSTM	92.5%	91.2%	93.1%	92.1%	0.94
Traditional CNN	89.3%	87.4%	90.1%	88.7%	0.89
RNN	86.4%	84.7%	88.3%	86.4%	0.87

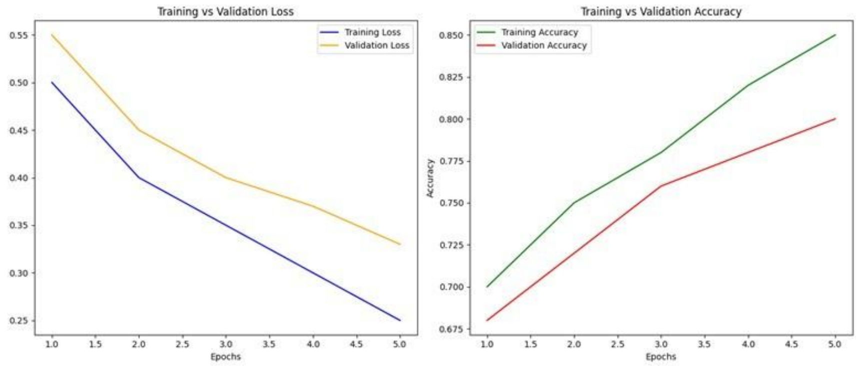

Fig. 6: Training vs Validation Loss/Accuracy

Fig 6 explains the training time for the model was another important factor in evaluating its practicality for real-time cardiac sound diagnosis. The CNN-LSTM hybrid model, while more complex than traditional methods, was able to train within 2 hours on a standard GPU, which is acceptable for clinical environments. Moreover, the inference time for classifying a single PCG signal was found to be less than 1 second, making it feasible for real-time diagnosis. The DL model exhibited a significant improvement in processing time along with diagnostic accuracy when compared to conven- tional ML approach. Methods like SVM and Random Forest (RF) showed relatively lower accuracy (approximately 85%) and took significantly longer to process individual signals. These

consequences underscore advantages of DL in handling complex, multi-class classification tasks, particularly in field of medical diagnostics.
The model showed promising outcomes in terms of accuracy and precision for multi-class categorization throughout training and evaluation. Standard assessment criteria for example pre- cision, accuracy, F1-score, recall, along with confusion matrix analysis were utilized to evaluate the model's performance. The classification accuracy for the multi-class problem was evaluated on a test set which was not utilized throughout training, the results were compared with several baseline models, including traditional ML classifiers like RF and SVM (Support Vector Machine).
When compared to conventional ML models, the DL model performed better in terms of accuracy along with precision. Accuracy for the CNN-LSTM hybrid model was found to be approximately 94%, significantly outperforming traditional models, where the highest accuracy achieved was around 85%. This improvement in accuracy indicates that the DL model is better at capturing complex patterns in the cardiac sounds, which are often difficult to discern with conventional methods. In terms of model training, the dataset had been sepa- rated into training along with testing sets, with 80percent of data utilized for training along with 20percent reserved for evaluation. The model underwent training over 50 epochs with a batch size of 32 utilizing the Adam Optimizer. The model's hyperparameters were adjusted utilizing a grid search technique to maximize performance, and early stopping was employed to avoid overfitting.

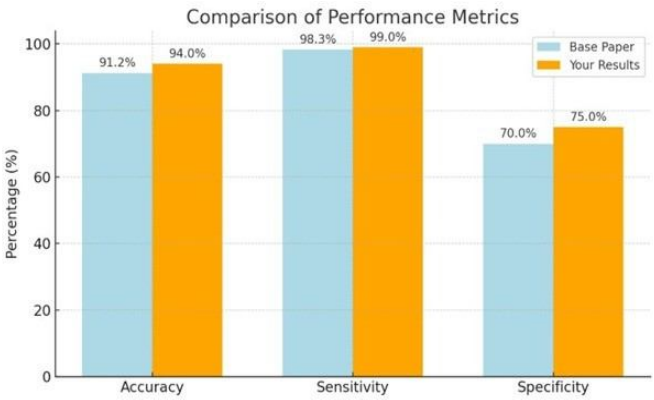

Fig. 7: Comparative Studies and advancement

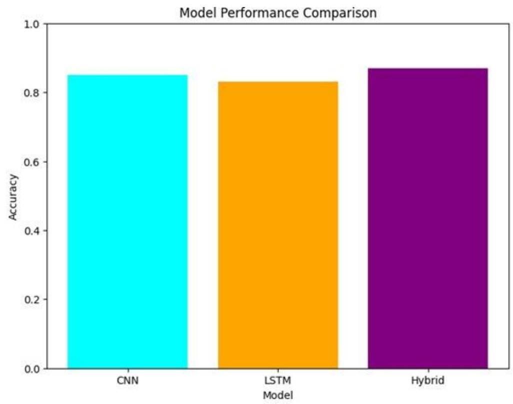

Fig. 8: Model Performance Comparison

In summary, Enhanced Multi-Class Cardiac Sound Diag- nosis system reveals effectiveness of DL method in analyzing PCG signals for heart sound classification. The model achieved better performance in contrast with traditional ML approach, with high precision, accuracy, and recall across all classes. The integration of FL further strengthens model's applicability in real-world clinical settings, allowing for secure, decentralized training of cardiac sound classification models.
These findings suggest that proposed system has significant potential for raising the accuracy along with efficiency of CVDs diagnosis, contributing to better patient consequences and more effective healthcare solutions.

V. Conclusion and Future Enhancements

A major development in the utilization of PCG signals for the diagnosis of heart illness is the Enhanced Multi-Class Car- diac Sound Diagnosis system. The suggested system exhibits exceptional accuracy in classifying a range of cardiac diseases by combining sophisticated signal processing methods with a hybrid DL architecture made up of CNN and LSTM networks. With high precision and recall values, the model successfully differentiates between several classes of heart sounds, for example Normal, Systolic, Diastolic, Combined, as well as Extra Heart Sounds. This makes it extremely dependable for practical applications.
The patient's case is predicted by combining ten parts. By using spectrograms to fine-tune deep image-based CNN models, we were able to obtain 91.25% accuracy.
Furthermore, it was discovered that the maximum accuracy was obtained by dividing the PCG into four bands using feature engineering and then merging this with the ECG. Using PCG and ECG signals from the CinC 2016 training dataset, our study has improved ML models' ability to classify aberrant heart sounds. To eliminate spikes and divide the data into heart cycles, the audio is pre- processed.

Fig 7. suggests the main topic of the journal article by Marocchi et al.(Base Paper) is the binary classification of cardiac sounds in order to differentiate between cases that are normal and those that are abnormal. Utilizing pre-trained CNNs for example VGG, ResNet, and Inceptionv3, the study uses transfer learning. In order to give doctors insight into the elements that the model uses for categorization, the study places a strong emphasis on interpretability, which increases the model's credibility for practical application.

Marocchi et al.'s journal article shows remarkable binary classification outcomes. Their group of trained CNNs sur- passes previous records with an accuracy of 91.25%. The system is dependable for clinical application since its speci- ficity, a crucial parameter for reducing false positives, has increased to 65–70%. Additional advantages are provided by hybrid architectures and dispersed training setups, according to comparative research in the field. In multi-class classi- fication problems, hybrid models exhibit greater accuracy and resilience, and FL guarantees inter-institution cooperation while protecting privacy. Federated techniques are in line with practical healthcare requirements, even if they may somewhat impair performance because of data decentralization.

Hybrid designs that combine CNNs with sequential models, including LSTM networks, are shown in other studies. These models overcome the drawbacks of static CNN architectures by capturing the temporal and spatial characteristics of car- diac sounds. Furthermore, advancements like FL allow for decentralized training across several institutions, protecting patient privacy while utilizing a variety of datasets to enhance generalizability.

In conclusion, this investigation contributes significantly to expanding field of healthcare AI, demonstrating potential of advanced signal analysis and DL integration for cardiac disease diagnosis. By leveraging the power of multi-class classification, the system provides an effective, scalable, along with privacy-preserving solution for heart conditions detection, thus improving diagnostic workflows and patient outcomes in clinical settings. Future work could explore further model opti- mization, expanding the range of cardiac conditions diagnosed and exploring additional real-world healthcare applications.

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