CHAPTER 1

INTRODUCTION

In this project, we propose a novel approach that integrates Deep Learning algorithms with IoT-based cardiac biosensors to answer the urgent demand for improved cardiovascular health monitoring. Our strategy focuses on non-invasive, real-time monitoring for the early identification of cardiotoxicity, with a focus on the prediction of cardiac troponin levels and the detection of arrhythmias. We guarantee predictability in the model by incorporating Explainable AI approaches. Our ultimate objective is to create an Internet of Things wearable that will enable continuous monitoring and maybe transform the treatment of cardiovascular disease.

1.1 CARDIOTOXICITY

Cardiotoxicity refers to the potential of certain drugs, chemicals, or toxins to cause damage to the heart muscle, leading to impaired cardiac function. This can manifest as arrhythmias, decreased cardiac output, or even heart failure. Many commonly used medications, including chemotherapy drugs, antibiotics, and antipsychotics, have been associated with cardiotoxic effects. Additionally, substances like alcohol and illicit drugs can also contribute to cardiotoxicity. Monitoring for signs such as chest pain, shortness of breath, and irregular heartbeats is crucial when using medications or substances known to have cardiotoxic properties. Early detection and intervention are essential in managing cardiotoxicity and minimizing its impact on cardiovascular health.

1.2 CURRENT CHALLENGES IN DETECTING CARDIOTOXICITY

Current challenges in monitoring cardiotoxicity include the difficulty in early detection due to asymptomatic or nonspecific symptoms, the lack of highly specific biomarkers, the invasiveness and limitations of traditional monitoring techniques, the need for continuous monitoring, and the complexity of integrating data from various sources. Overcoming these challenges requires innovative approaches leveraging technology and data analytics to enable non-invasive, real-time monitoring for timely intervention and improved patient outcomes.

1.3 ELECTROCARDIOGRAM

A 12-lead electrocardiogram (ECG) provides a comprehensive assessment of the heart's electrical activity, aiding in the identification of cardiotoxicity. By analysing the ECG waveform patterns and intervals, the abnormalities indicative of cardiotoxic effects, such as arrhythmias, myocardial infarction can be detected. Monitoring changes in the ECG over time enables early detection of cardiotoxicity, facilitating timely interventions and adjustments to treatment regimens to mitigate adverse effects on the heart.

1.4 DEEP LEARNING METHODS

Deep learning has emerged as a powerful paradigm in healthcare, particularly in the analysis of medical imaging data such as electrocardiogram (ECG) images. It's can automatically learn intricate patterns and features directly from raw data, without the need for manual feature engineering. This capability is particularly advantageous in ECG analysis, where subtle abnormalities can signify significant cardiac conditions.

1.4.1 CONVOLUTIONAL NEURAL NETWORK

CNNs excel in ECG analysis by efficiently extracting hierarchical features from signal images, capturing intricate patterns crucial for diagnosis. Their ability to discern spatial hierarchies enables detection of both local anomalies and global trends in data. Moreover, CNNs facilitate transfer learning, leveraging pre-trained models to enhance performance, particularly valuable in scenarios with limited labelled data.

1.4.2 VGG-16

VGG-16, with 13 convolutional layers and 3 fully connected layers, organizes convolutions into blocks with subsequent max-pooling layers for down sampling. Its deep architecture efficiently captures features from ECG images, aiding in identifying subtle abnormalities. The homogeneous structure simplifies model design and interpretation, facilitating clearer understanding of learned representations. VGG networks excel in capturing increasingly abstract features, crucial for detecting underlying cardiac conditions.

1.4.3 MOBILENET

MobileNet, with 28 layers, employs depth-wise separable convolutions, reducing parameters and computational cost. Its lightweight design suits resource-constrained environments, like mobile devices and wearable sensors. This enables real-time ECG analysis, facilitating continuous monitoring and prompt intervention. MobileNet's efficiency in edge computing ensures privacy and minimal latency, enhancing accessibility and scalability in healthcare applications.

1.5 EXPLAINABLE AI

Explainable Artificial Intelligence (XAI) is a critical area of research aimed at enhancing the transparency, interpretability, and trustworthiness of AI systems, particularly in complex domains such as healthcare. In general, XAI techniques enable humans to understand the reasoning behind AI-driven decisions by providing insights into the internal workings of the models. This is achieved through various methods, including visualization techniques like heatmaps and saliency maps, which highlight important features in the input data that contribute to model predictions.

1.6 OBJECTIVES

The main objectives of this project are,

1. To detect Arrythmia from the abnormalities in ECG.
2. To utilize Deep Learning (DL) algorithms to find the biomarkers for cardiotoxicity.
3. To enable real-time predictions of heart functions for timely interventions and improved healthcare outcomes.
4. To integrate Explainable Artificial Intelligence (XAI) techniques for interpretation and explainability of the model's predictions.
5. To integrate the trained model into an IoT wearable device for continuous monitoring and early detection of cardiovascular abnormalities.
6. To develop a web-based product capable of generating predictions on ECG reports for diagnostic purposes.

CHAPTER 2

LITERATURE SURVEY

Umer M et al. (2022) present an IoT-based smart monitoring system for patients with acute heart failure, leveraging sensors for heart rate, blood pressure, temperature, glucose, cholesterol, and ECG signals. The study compares CNN, RNN, MLP, and LSTM models, with CNN achieving 92.89% accuracy. Transfer learning with VGG16 and AlexNet is also explored, highlighting CNN's superiority. Limitations include dataset imbalance [1].

Yıldırım Ö et al. (2018) propose a method for arrhythmia detection using a deep CNN with 16 layers, achieving 91.33% accuracy on long-duration ECG signals. The focus is on reducing computational complexity, but the study analyses a small number of ECG signal fragments, limiting its scope [2].

Khan MA (2020) presents an IoT framework for heart disease prediction using a modified deep CNN and the Elephant Herd Optimization Algorithm. However, the study uses pseudo numbers for some features, limiting its real-world applicability [3].

Mesitskaya DF et al. (2024) detect cardiotoxicity in cancer patients using a single-lead ECG, focusing on left ventricular diastolic dysfunction, atrial fibrillation, and QTc prolongation. The study uses the CardioQvark mobile phone cover with an integrated ECG sensor but does not include patients with intermediate and low LVEF [4].

Wang et al. (2022) propose a wearable ECG monitor, IREALCARE, with integrated sensors and Bluetooth transmission for real-time cardiovascular disease detection. Limitations include reliance on optimal confidence level selection [5].

Dami S et al. (2021) predict cardiovascular events using LSTM-DBN, achieving 88.42% accuracy. The approach combines LSTM for long-term dependencies and DBN for feature selection but requires high computational efficiency and memory [6].

Cañón-Clavijo RE et al. (2023) develop an IoT-based system for heart monitoring and arrhythmia detection, achieving 97% accuracy with k-nearest neighbors. However, the study lacks discussion on robustness to noise and ECG signal variability [7].

Raj S (2020) present an IoT-based platform for remote real-time cardiac activity monitoring, using Pan Tompkin's algorithm for R-peak detection and twin support vector machines for classification. Limitations include the need for more specific feature selection based on R-wave morphology [8].

Ma S et al. (2022) propose deep learning-based data augmentation and model fusion for arrhythmia identification, achieving 99.4% accuracy. The study employs ECG-GAN for data augmentation and ResNet BiLSTM-Attention for classification. Limitations include the integration of ResNet and BiLSTM models which introduces complexity [9].

Abubaker MB et al. (2023) introduces a lightweight Convolutional Neural Network (CNN) model for predicting four major cardiac abnormalities. The study investigates transfer learning using SqueezeNet and AlexNet and proposes a new CNN architecture for cardiac abnormality prediction achieving 99.79% accuracy. Limitations include training and testing time for SquuezeNet based algorithm is longer, optimization algorithms are not used to determine the value of hyperparameters [10].

Y. Yang et al. (2018) aims to enhance the explainability of neural networks in healthcare by employing the Layer-wise Relevance Propagation algorithm to elucidate clinical decisions made by deep neural networks. By highlighting the features contributing to probabilistic therapy decisions for individual patients, this algorithm facilitates interpretability. LRP provides insights into feature relevance, it may not fully capture the dynamic and temporal nature of clinical data [11].

Atul Anand et al. (2022) proposed ST-CNN-GAP-5 model exhibits promising performance on the PTB-XL dataset. Although SHapley Additive exPlanations (SHAP) offer insights for the model prediction, validation by clinical experts could enhance interpretability. Limitations of SHAP includes the ability to capture the full complexity of interactions in highly nonlinear models [12].

CHAPTER 3

PROPOSED WORK

3.1 INTRODUCTION

The proposed solution involves the development of a comprehensive cardiotoxicity detection system using 12-lead ECG images as input. This system aims to address the challenges in early detection of cardiovascular abnormalities, including arrhythmias and myocardial infarction (MI), by leveraging deep learning models and Explainable Artificial Intelligence (XAI) techniques.

Initially, a diverse dataset containing normal, abnormal, MI, and history of MI ECG images will be pre-processed to ensure consistency and quality. Subsequently, three deep learning models - Convolutional Neural Network (CNN), MobileNet, and VGG - will be trained on the pre-processed dataset for ECG image classification. Each model will be optimized to extract relevant features from the ECG images, enabling accurate detection of cardiotoxicity.

To further enhance detection accuracy, a fusion model will be developed to combine the predictions of the individual CNN, MobileNet, and VGG models. Additionally, Explainable Artificial Intelligence (XAI) techniques, such as saliency map will be integrated into the system to provide interpretability and transparency for the model predictions. Saliency map visualizations will highlight the regions of interest in the ECG images contributing to the model's decisions, aiding clinicians in understanding and trusting the model's outputs.

Finally, the trained models will be integrated into an IoT-based wearable device for real-time monitoring of cardiovascular health. This device will enable continuous monitoring of ECG signals, allowing for early detection of abnormalities and timely interventions to improve patient outcomes.

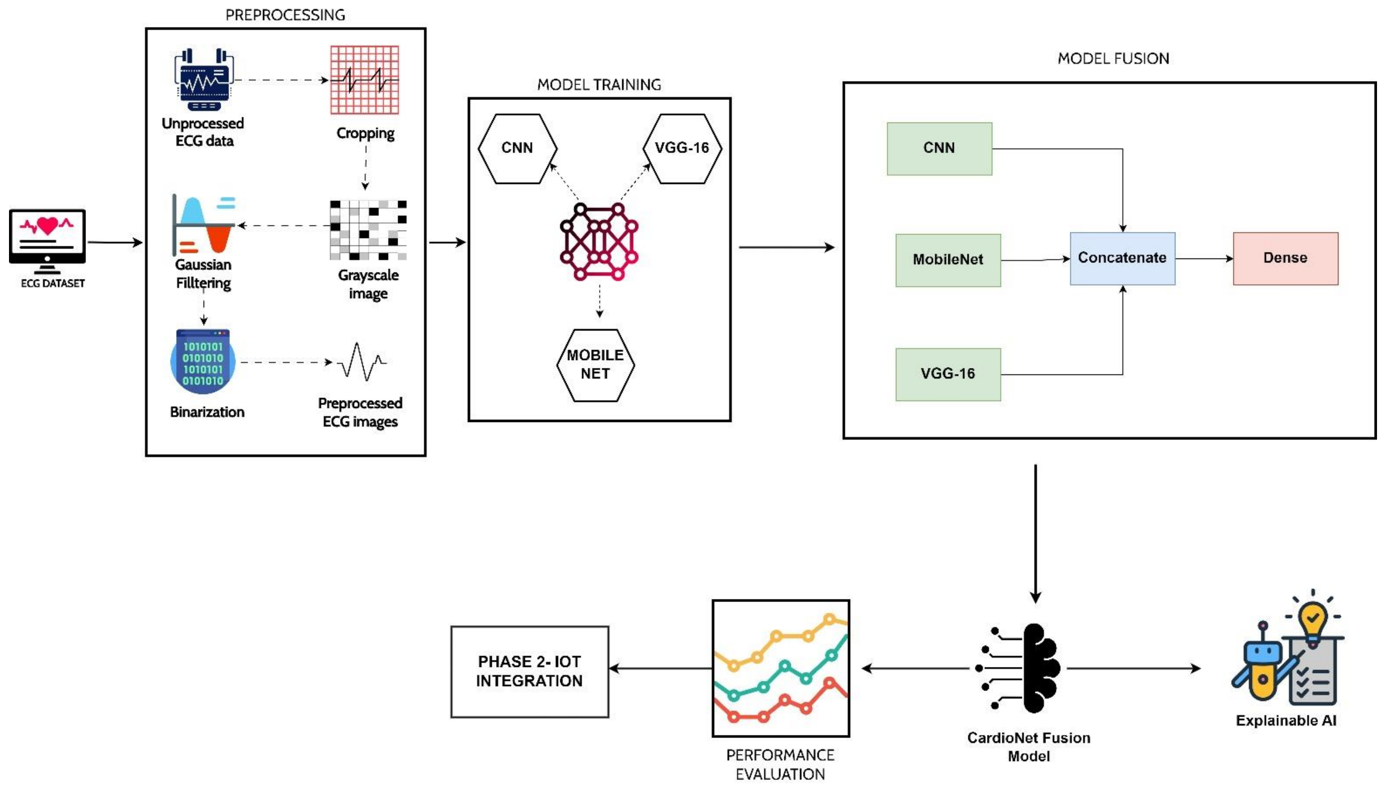

Fig:1. Architecture diagram of Proposed System

3.2 MODULES

The proposed system is divided into 5 main modules

1. Data preprocessing
2. Model training using Deep Learning models
3. Model fusion
4. Explainable AI using GradCAM
5. Web product and IoT integration

3.2.1 DATA PREPROCESSING

Data preprocessing is a critical initial phase in readying data for deep learning. In ECG image analysis, it involves essential steps like grayscale conversion, Gaussian blur, thresholding, and binarization. These steps collectively enhance data quality by simplifying representation, smoothing irregularities, and highlighting ECG signals for improved model interpretation.

3.2.2 MODEL TRAINING USING DEEP LEARNING MODELS

Model training using deep learning models is a crucial component of cardiotoxicity detection project. This module involves the development and training of Convolutional Neural Networks (CNNs), MobileNet, and VGG models to analyze preprocessed ECG images and detect cardiac abnormalities. Each model is tailored to extract relevant features from the input data, leveraging the hierarchical representations learned during training to accurately classify ECG images into different categories (normal, abnormal, MI, etc.). The training process involves feeding the preprocessed ECG images into the models and iteratively adjusting the model parameters to minimize the prediction error. Techniques such as transfer learning and fine-tuning are employed to optimize model performance, particularly in cases where labeled training data is limited. Through rigorous training and validation, these deep learning models learn to recognize patterns and anomalies in ECG signals, enabling accurate detection of cardiotoxicity.

3.2.3 MODEL FUSION

Model fusion is a key strategy employed to improve the robustness and performance of the cardiotoxicity detection system. In this module, the predictions from multiple deep learning models, including CNNs, MobileNet, and VGG are combined to leverage their complementary strengths and enhance overall predictive accuracy. By fusing the predictions from multiple models, we aim to mitigate the limitations of individual models and achieve greater reliability and generalization in cardiotoxicity detection. This fusion approach ensures that our system can effectively capture diverse patterns and abnormalities in ECG signals, leading to more accurate and reliable diagnoses.

3.2.4 EXPLAINABLE AI USING SALIENCY MAP

Explainable Artificial Intelligence (XAI) techniques, such as saliency mapping, play a crucial role in enhancing the interpretability and transparency of our cardiotoxicity detection system. In this module, saliency mapping is utilized to provide visual explanations for the predictions made by our deep learning models. By highlighting the regions of interest in the input ECG images that contribute most to the model's decision-making process, saliency mapping offers valuable insights into how the models identify and classify cardiac abnormalities. These visual explanations not only enhance the trust and understanding of our models among healthcare practitioners but also enable clinicians to interpret and validate the model predictions in real-world scenarios. Through the integration of saliency mapping, the cardiotoxicity detection system becomes more transparent, interpretable, and clinically relevant, ultimately improving patient care and outcomes.

3.2.5 WEB PRODUCT AND IOT INTEGRATION

The Web Product and IoT Integration module focuses on deploying our cardiotoxicity detection system into practical healthcare settings. In this module, we develop a user-friendly web-based interface that allows healthcare professionals to upload ECG images, visualize model predictions, and access interpretability features such as saliency map visualizations. Additionally, we integrate our detection system with IoT-based cardiac biosensors and wearable devices for real-time monitoring of cardiovascular health. This integration enables continuous data collection and analysis, facilitating early detection of cardiac abnormalities and timely interventions. By providing seamless access to our detection system through web and IoT platforms, we aim to improve accessibility, scalability, and usability in clinical settings, ultimately enhancing patient care and outcomes.

CHAPTER 4

IMPLEMENTATION

4.1 TOOLS REQUIRED

The following packages are required for detection of cardiotoxicity

4.1.1 Tensorflow

TensorFlow is an open-source machine learning framework developed by Google, widely used for building and training various deep learning models. It provides a comprehensive ecosystem of tools, libraries, and resources for machine learning research and production deployment.

4.1.2 Keras

Keras is a high-level neural networks API, originally developed as part of the TensorFlow project, but now a standalone library. It allows for easy and fast experimentation with deep learning models, offering a user-friendly interface and seamless integration with TensorFlow, facilitating rapid prototyping and model deployment.

4.1.3 Matplotlib

A comprehensive library for creating static, animated, and interactive visualizations in Python. It is commonly used for plotting various types of data such as line plots, histograms, scatter plots, etc., making it essential for data analysis and presentation.

4.1.4 Numpy

A fundamental package for scientific computing in Python. It provides support for multi-dimensional arrays and matrices, along with a variety of mathematical functions to operate on these arrays efficiently. NumPy is essential for numerical computations in fields like machine learning, physics, engineering, and more.

4.1.5 ScikitLearn

Scikit-learn offers simple and efficient tools for data mining and data analysis, with support for various supervised and unsupervised learning algorithms, including classification, regression, clustering, dimensionality reduction, and more.

4.1.6 ScikitImage

Scikit-image provides a collection of algorithms for image processing tasks such as segmentation, feature extraction and morphological operations. It is widely used in fields like computer vision, medical imaging, and remote sensing.

4.1.7 SeaBorn

A data visualization library based on matplotlib, providing a high-level interface for creating attractive and informative statistical graphics. Seaborn simplifies the process of creating complex visualizations by providing built-in functions for tasks like plotting univariate and bivariate distributions, visualizing linear relationships, and more. It is particularly useful for exploratory data analysis and presenting insights from data.

4.1.8 Google Colab

Google Colab is a cloud-based Jupyter notebook environment by Google, enabling collaborative Python coding in the browser. It offers free access to GPU and TPU resources for training deep learning models, with seamless integration with Google Drive.

4.1.9 Gradio

Gradio is an open-source Python library designed to create UIs for machine learning models with minimal code. It simplifies the process of deploying and sharing models by providing a straightforward interface for creating interactive web applications.

4.2 RUNTIME ENVIRONMENT

Google colab is used to run and test the code in basic runtime type. The Basic runtime is the default runtime and is free to use. The basic runtime type consists of 1 core CPU of 12GB RAM and 0.5GB GPU. The colab environment runtime is connected to the google drive where the dataset is available.

4.3 DATA PREPROCESSING

Data preprocessing is crucial in deep learning tasks.The preprocessing module enhances the quality of ECG images for analysis.The preprocessing steps includes conversion to grayscale, gaussian blur, thresholding and binarization. Converting the RGB images to grayscale simplifies the representation of the data, reducing computational complexity while retaining essential information for analysis. The application of Gaussian blur helps to smooth out irregularities and noise present in the images, creating a more uniform background that facilitates feature extraction. Otsu's thresholding method automatically determines the optimal threshold for binarizing the blurred images, effectively separating the ECG signals from the background and enhancing contrast for better feature detection. Finally, binarization transforms the grayscale images into binary representations, where ECG signals are distinctly highlighted against the background, making them more suitable for interpretation by the deep learning models. Together, these preprocessing steps collectively enhance the quality of the ECG images and providing cleaner and more informative input data for the models.

Algorithm 1 Preprocessing 12-Lead ECG Image

Input: 12 lead ECG image ($input\_image$)
Output: Preprocessed ECG image

procedure PREPROCESSECG($input\_image$)
    Crop the 12-lead ECG image:
        $cropped\_image - input\_image.crop(x_{left}, x_{top}, x_{right}, x_{bottom})$
    Convert ECG image to grayscale:
    $grayscaled\_image - rgb2gray(cropped\_image)$
    Apply Gaussian blur with sigma value 0.7:
    $blurred\_image - gaussian(grayscaled\_image, \sigma = 0.7)$
    Apply Otsu thresholding:
    $threshold - threshold\_otsu(blurred\_image)$
    $binary\_image - blurred\_image < threshold$
    return binary_image
end procedure

4.4 MODEL TRAINING USING DEEP LEARNING MODELS

Model training is a critical component of the cardiotoxicity detection system, involving the utilization of deep learning architectures such as Convolutional Neural Networks (CNNs), MobileNet, and VGG. This process begins with the preparation of the input data, which consists of a diverse dataset containing electrocardiogram (ECG) images representing various cardiac conditions, including normal, abnormal, and myocardial infarction (MI).

Subsequently, the selected deep learning architectures (CNN, MobileNet, VGG) are instantiated and configured to accept the preprocessed ECG images as input. Each architecture is initialized with weights either randomly or pre-trained on large-scale image datasets such as ImageNet to leverage transfer learning and accelerate convergence. Custom output layers are added to adapt the architectures for the specific classification task of cardiotoxicity detection.

The models are compiled using appropriate optimizers such as Adam or SGD, with specified learning rates and loss functions tailored to the classification task. To monitor and optimize the training process, various callbacks are defined, including ModelCheckpoint to save the best-performing model weights, ReduceLROnPlateau to adjust the learning rate dynamically based on validation loss, and EarlyStopping to prevent overfitting.

The models are then trained using the prepared training data, with validation data used for evaluating performance at each epoch. Upon completion of training, the trained models are evaluated on a separate test dataset to assess their generalization performance. Model predictions are generated for the test data, and accuracy metrics are computed to quantify the models' classification performance.

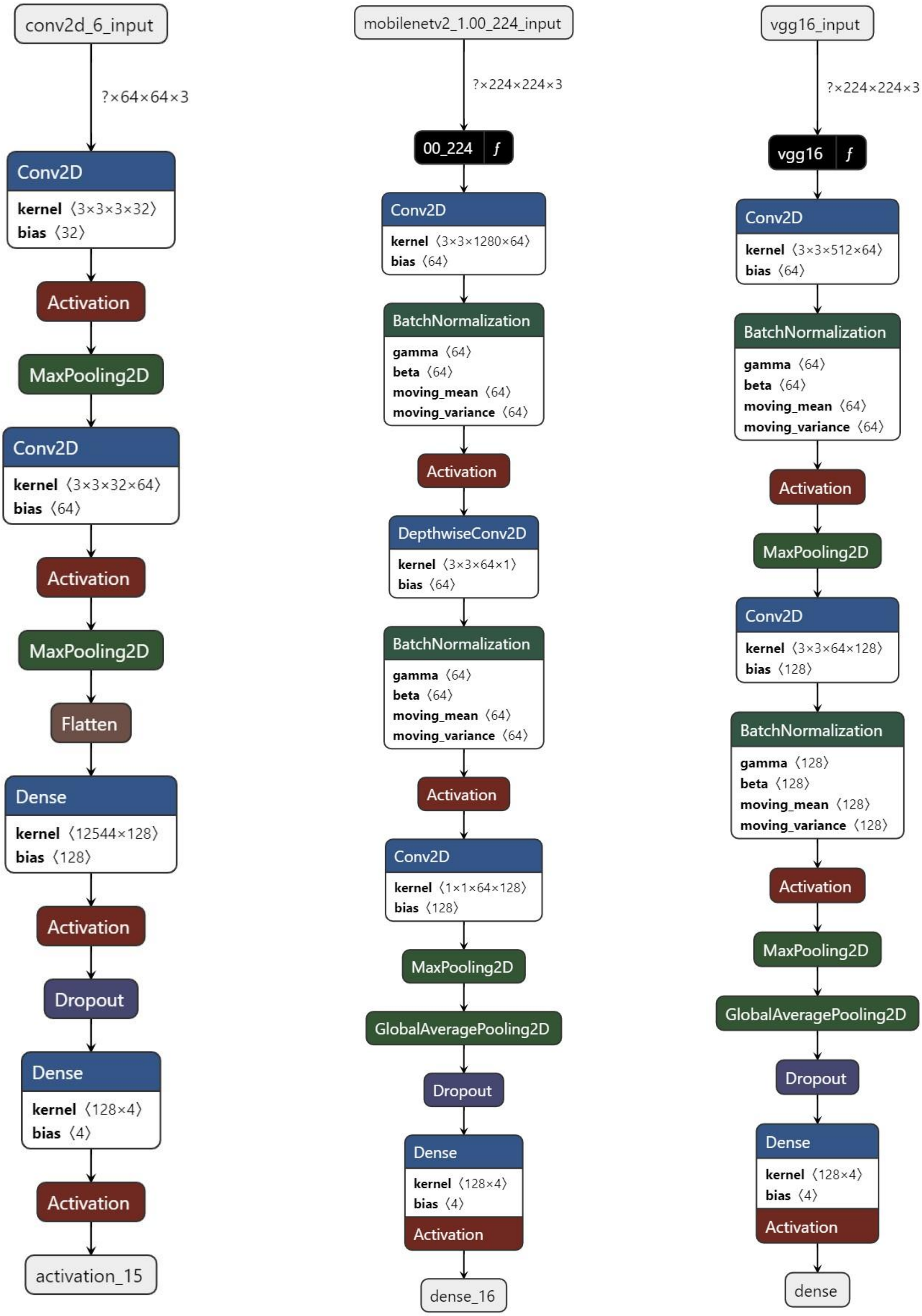

Fig:2 Architecture of Deep Learning models

Algorithm 2 Model Training

Input: Preprocessed ECG image (X, y), No.of classes ($num\_classes$), No.of epochs (num_epochs), Batch size ($batch\_size$), Learning rate ($learning\_rate$)
Output: Trained Model

procedure TRAINMODEL(X, y, $num\_classes$, num_epochs, $batch\_size$, $learning\_rate$)
    Import necessary modules
    Split the input data into train and test sets:
    X_{train}, X_{test}, y_{train}, y_{test} - train_test_split(X, y, test_size=0.2)
    Setup the pipeline steps:
    Compile the model using Adam optimizer:
    $optimizer$ - Adam($learning\_rate$)
    model.compile(optimizer=$optimizer$, loss='categorical_crossentropy', metrics=['accuracy'])
    Define callbacks for model training:
    checkpoint - ModelCheckpoint("best_model.h5", monitor='val_accuracy', verbose=1, save_best_only=True, mode='max')
    reduce_lr - ReduceLROnPlateau(monitor='val_loss', factor=0.2, patience=3, min_lr=0.0001, verbose=1)
    early_stop - EarlyStopping(monitor='val_loss', patience=5, restore_best_weights=True)
    Train the model:
    history - model.fit(X_{train}, y_{train}, num_epochs, $batch\_size$, validation_data=(X_{test}, y_{test}), callbacks=[checkpoint, reduce_lr, early_stop])
    Predict the labels of the test set:
    y_{pred} - model.predict(X_{test})
    Compute accuracy:
    accuracy - accuracy_score(y_{test}, y_{pred})
    Generate accuracy and classification report
end procedure

4.5 MODEL FUSION

The model fusion technique employed in this project is a method of combining the predictions of multiple machine learning models to enhance the overall performance of our cardiotoxicity detection system. This approach is based on the principle that different models may capture different aspects of the underlying data distribution, and by combining their predictions, we can achieve improved accuracy and robustness.

Specifically, our model fusion process involves integrating the outputs of three distinct deep learning models: a Convolutional Neural Network (CNN), MobileNet, and VGG. Each of these models has been trained on preprocessed electrocardiogram (ECG) images to extract relevant features indicative of cardiotoxicity.

To perform model fusion, we first preprocess the input data, consisting of preprocessed ECG images and their corresponding labels. We then split the data into training and testing sets to facilitate model evaluation. Next, we define a common input layer that serves as the entry point for all three models. This common input layer ensures consistency in the input dimensions across the different models. Subsequently, we connect each individual model to the common input layer and obtain their respective outputs. These outputs, representing the extracted features from the ECG images, are concatenated to create a unified feature representation. On top of this concatenated feature representation, we add a dense layer for classification, with the number of units equal to the total number of classes. This dense layer enables the fused model to predict the presence of cardiotoxicity based on the combined features extracted by the individual models.

The model is compiled with appropriate optimizer, loss function, and evaluation metrics. Additionally, callback functions are used to monitor the training process and prevent overfitting. The fused model is then trained using the training data, and its performance is evaluated on the testing data to assess its effectiveness in detecting cardiotoxicity.

The model fusion technique allows us to leverage the complementary strengths of multiple models and improve the accuracy and reliability of our cardiotoxicity detection system, ultimately contributing to better patient care and outcomes.

Algorithm 3 Fused Model Training

Input:
  Pre-trained models *mobilenet_model* , *vgg_model* and CNN.
  Image data generator *datagen* set up for training and validation data.
  Class labels list *classes*.
Output:
  Trained fused model saved as "fused_model.h5".
  Validation loss and accuracy metrics.
Rename layers of *mobilenet_model* and *vgg_model* to avoid naming conflicts.
for all layer in *mobilenet_model* **do**
  Set *layer.trainable* to False.
end for
for all layer in *vgg_model* **do**
  Set *layer.trainable* to False.
end for
mobilenet_output ← *mobilenet_model*'s second-to-last layer's output.
vgg_output ← *vgg_model*'s second-to-last layer's output.
$CNN \leftarrow CNN\_model$'s second-to-last layer's output.
Add dense layer with 64 units and ReLU activation to *mobilenet_output*.
Add dense layer with 64 units and ReLU activation to *vgg_output*.
Concatenate *mobilenet_output* and *vgg_output* into a fusion layer.
Add dense layer with 128 units and ReLU activation to the fusion layer.
Add output layer with softmax activation and number of units equal to length of *classes*.
Create fused model with inputs from *mobilenet_model* and *vgg_model* and output layer.
Compile the fused model using Adam optimizer and categorical cross-entropy loss.
Create training and validation generators using *datagen*.
Initialize custom generators for training and validation data.
Set training parameters:

- Epochs: 20
- Batch size: 32

Configure model callbacks such as ModelCheckpoint, ReduceLROnPlateau, and EarlyStopping.
Train the fused model using custom generators for training and validation data.
Evaluate the model on validation data and print loss and accuracy.
Save the trained fused model as "fused_model.h5".

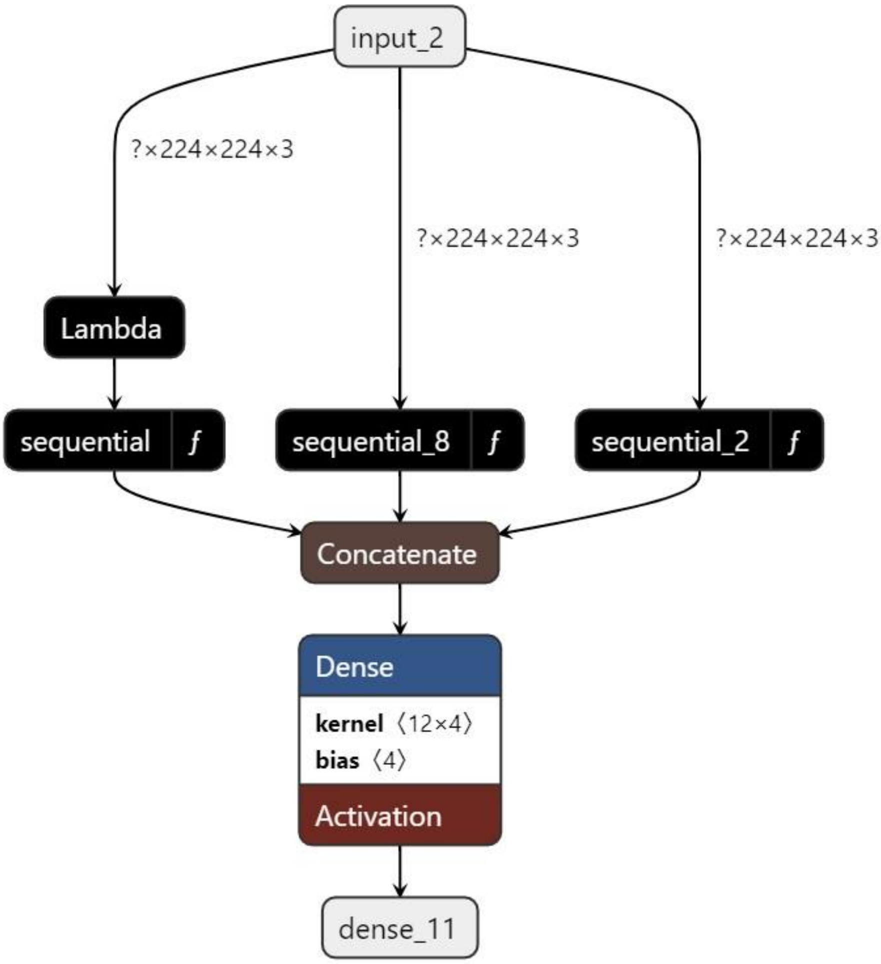

Fig: 3 CardioNetFusion Model Architecture

4.6 EXPLAINABLE AI USING SALIENCY MAP

The integration of Explainable AI (XAI) using saliency maps provides insights into our model's predictions for ECG images. After loading the pre-trained fusion model, a saliency map is generated to highlight the most important features influencing the model's decision. The saliency map is then visualized using a gradient-based approach, showing regions of the image that contribute most to the prediction. This allows us to not only predict the class of the ECG image but also understand why the model made that particular prediction, enhancing the interpretability and transparency of our AI system.

Algorithm 4 Grad-CAM Heatmap Generation

Input: Preprocessed input image (I), Trained CNN model (M), Target class index

Output: Grad-CAM heatmap (H)

procedure GENERATEGRADCAM(I, M, Target class index)

  Load the preprocessed input image I

  Pass the input image through the model M : $F = M(I)$

  Retrieve the final convolutional layer of the model M

  Compute the gradient of the target class score : $\frac{\partial L}{\partial A_j}$

  Compute the importance weights using global average pooling (GAP) : $w_k = \sum_{i=1}^{H} \sum_{j=1}^{W} \frac{\partial L}{\partial A_{ij}}$

  Compute the Grad-CAM heatmap: $H = \sum_k w_k F_k$

  Apply ReLU activation to the Grad-CAM heatmap: $H = ReLU(H)$

  Resize the Grad-CAM heatmap: $H = Resize(H, input\_size)$

  Normalize the Grad-CAM heatmap : $H = \frac{H - \min(H)}{\max(H) - \min(H)}$

  return Grad-CAM heatmap for interpretation: H

end procedure

4.7 WEB PRODUCT

The web product leverages Gradio, a Python library for creating UIs around machine learning models, which facilitates the upload of reports and obtain predictions along with saliency maps. Users can easily upload their reports through the web interface. Once uploaded, the report is processed by deep learning model in the backend. The model not only generates predictions based on the content of the report but also computes saliency maps to highlight the most influential parts of the report that contribute to the predictions. Gradio seamlessly integrates these functionalities into a user-friendly interface, allowing users to interact with the model effortlessly. This approach enables users to gain insights into the predictions made by the model and understand the underlying reasoning behind them through the visual interpretation provided by the saliency maps

CHAPTER 5

RESULTS AND ANALYSIS

Our proposed fusion model achieved high accuracy in detecting cardiotoxicity. The model attained accuracy of 96.5%

5.1 PREPROCESSED IMAGES

The preprocessing involved several key steps aimed at enhancing the quality and interpretability of the images. These steps included conversion to grayscale, Gaussian blur, thresholding, and binarization. Each step played a vital role in preparing the images for analysis by simplifying their representation, reducing noise, enhancing contrast, and highlighting relevant features.

Fig: 4 Preprocessed ECG image

5.2 DEEP LEARNING MODELS

Three separate deep learning models were trained to classify ECG images, and each model achieved high accuracy in its classification task. The CNN model attained an accuracy of 91.2%, demonstrating its robustness in distinguishing between different cardiac conditions. Similarly, VGG16 achieved an accuracy of 97.2%, indicating its effectiveness in accurately classifying ECG signals. Additionally, the MobileNet performed exceptionally well, achieving an accuracy of 98.6%, underscoring its ability to accurately classify ECG images. These high accuracy percentages across all three models highlight the efficacy of deep learning techniques in analyzing ECG data for cardiac condition diagnosis.

```
Epoch 27/50
24/24 [==============================] - ETA: 0s - loss: 0.4836 - accuracy: 0.8215
Epoch 27: val_accuracy did not improve from 0.85792
24/24 [==============================] - 18s 715ms/step - loss: 0.4836 - accuracy: 0.8215 - val_loss: 0.4846 - val_accuracy: 0.8306 - lr: 1.0000e-04
Epoch 28/50
24/24 [==============================] - ETA: 0s - loss: 0.4725 - accuracy: 0.8228
Epoch 28: val_accuracy did not improve from 0.85792
24/24 [==============================] - 20s 825ms/step - loss: 0.4725 - accuracy: 0.8228 - val_loss: 0.5474 - val_accuracy: 0.7814 - lr: 1.0000e-04
6/6 [==============================] - 3s 494ms/step - loss: 0.4938 - accuracy: 0.8306
Test Loss: 0.49380946159362793
Test Accuracy: 0.8306010961532593
```

Fig: 5 CNN Model Accuracy

```
Epoch 27/50
24/24 [==============================] - ETA: 0s - loss: 0.1038 - accuracy: 0.9678
Epoch 27: val_accuracy improved from 0.98361 to 0.98907, saving model to /content/drive/MyDrive/Model/best_vgg16_model(2).h5
24/24 [==============================] - 23s 981ms/step - loss: 0.1038 - accuracy: 0.9678 - val_loss: 0.0819 - val_accuracy: 0.9891 - lr: 1.0000e-05
Epoch 28/50
24/24 [==============================] - ETA: 0s - loss: 0.1103 - accuracy: 0.9544
Epoch 28: val_accuracy did not improve from 0.98907
24/24 [==============================] - 20s 845ms/step - loss: 0.1103 - accuracy: 0.9544 - val_loss: 0.0863 - val_accuracy: 0.9727 - lr: 1.0000e-05
6/6 [==============================] - 3s 549ms/step - loss: 0.0946 - accuracy: 0.9781
Test Loss: 0.09460731595754623
Test Accuracy: 0.9781420826911926
```

Fig: 6 VGG16 Model Accuracy

```
Epoch 32/50
24/24 [==============================] - ETA: 0s - loss: 0.2243 - accuracy: 0.9248
Epoch 32: val_accuracy improved from 0.92350 to 0.92896, saving model to /content/drive/MyDrive/best_mobilenet_model1.h5
24/24 [==============================] - 78s 3s/step - loss: 0.2243 - accuracy: 0.9248 - val_loss: 0.2212 - val_accuracy: 0.9290 - lr: 1.0000e-04
Epoch 33/50
24/24 [==============================] - ETA: 0s - loss: 0.2199 - accuracy: 0.9342
Epoch 33: val_accuracy did not improve from 0.92896
24/24 [==============================] - 75s 3s/step - loss: 0.2199 - accuracy: 0.9342 - val_loss: 0.3077 - val_accuracy: 0.9235 - lr: 1.0000e-04
6/6 [==============================] - 13s 2s/step - loss: 0.2417 - accuracy: 0.9454
Test Loss: 0.24172227084636688
Test Accuracy: 0.9453551769256592
```

Fig: 7 MobileNet Model Accuracy

5.3 CARDIONET FUSION MODEL

The results obtained from the Cardionet fusion model, which integrates CNN, VGG, and MobileNet architectures, are highly promising, showcasing an impressive accuracy of 96.7%. This accuracy demonstrates the effectiveness of leveraging multiple deep learning models to enhance the classification of ECG images. The fusion of these architectures enables the model to capture diverse features and patterns present in the ECG images, thereby improving its overall performance.

```
Epoch 37: ReduceLROnPlateau reducing learning rate to 1e-05.
24/24 [==============================] - 20s 829ms/step - loss: 0.2527 - accuracy: 0.9705 - val_loss: 0.2374 - val_accuracy: 0.9836
Epoch 38/50
24/24 [==============================] - ETA: 0s - loss: 0.2649 - accuracy: 0.9651
Epoch 38: val_accuracy did not improve from 0.98907
24/24 [==============================] - 21s 884ms/step - loss: 0.2649 - accuracy: 0.9651 - val_loss: 0.2394 - val_accuracy: 0.9836
Epoch 39/50
24/24 [==============================] - ETA: 0s - loss: 0.2360 - accuracy: 0.9839
Epoch 39: val_accuracy did not improve from 0.98907
24/24 [==============================] - 20s 853ms/step - loss: 0.2360 - accuracy: 0.9839 - val_loss: 0.2323 - val_accuracy: 0.9836
```

Fig: 8 CardioNet Fusion Model Accuracy

5.3.1 AREA UNDER RECEIVER OPERATING CHARACTERISTIC (AUROC) CURVE

The AUROC (Area Under the Receiver Operating Characteristic) curve analysis for the Cardionet fusion model across the four classes reveals compelling insights into its classification performance. With an AUROC curve, each class's true positive rate (sensitivity) is plotted against its false positive rate (1-specificity), providing a comprehensive evaluation of the model's ability to distinguish between different classes. The AUROC curve illustrates the model's discriminative power, with values closer to 1 indicating superior performance. In the case of the Cardionet fusion model, the AUROC curve demonstrates robust discrimination across all four classes, with each class exhibiting a high AUROC score, further validating the model's effectiveness in accurately classifying ECG images.

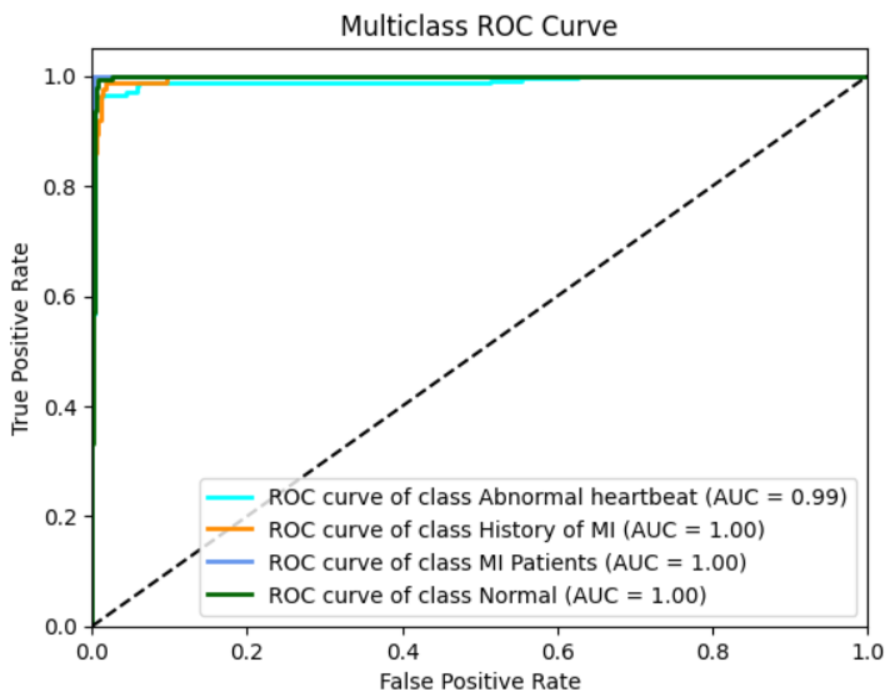

Fig: 9 AUROC curve of CardioNet Fusion Model

5.3.2 CONFUSION MATRIX

The confusion matrix serves as a critical tool for assessing the performance of our Cardionet fusion model in predicting cardiotoxicity across four distinct classes: "Abnormal heartbeat," "MI Patients," "History of MI," and "Normal." It offers a comprehensive summary of the model's predictions against the actual labels present in the test dataset. Each row and column in the matrix corresponds to one of these four classes, with the cells representing the count of instances where the actual class (row) aligns with the predicted class (column).

By analyzing the confusion matrix, we gain insights into how effectively the model distinguishes between different cardiotoxicity categories. It highlights instances where the model accurately classifies cardiotoxicity cases and areas where misclassifications occur.

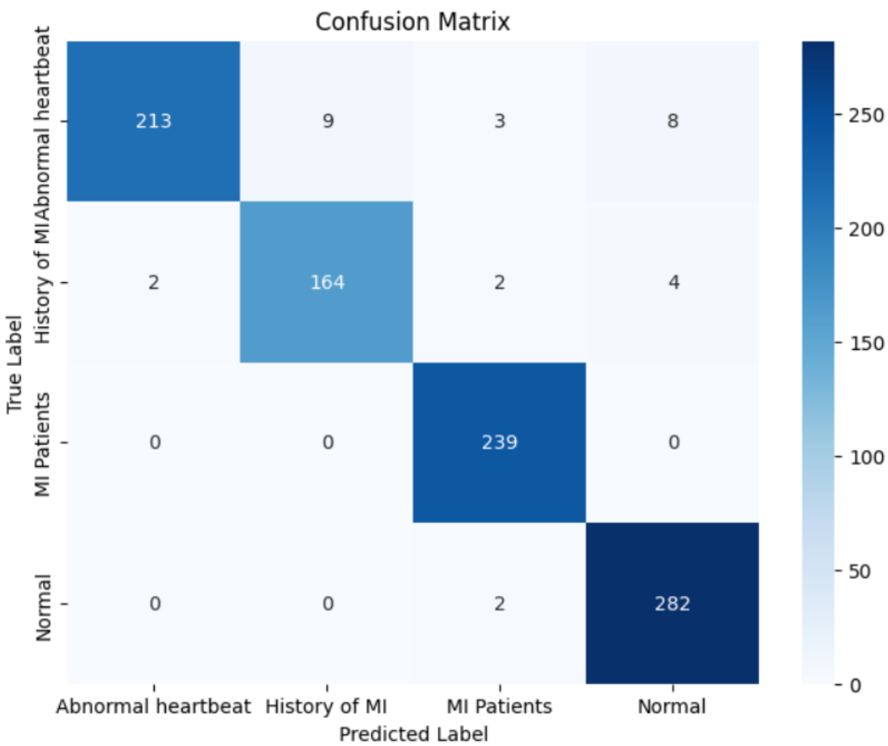

Fig: 10 Confusion matrix of CardioNet Fusion Model

5.3.3 CLASSIFICATION REPORT

The classification report complements the insights provided by the confusion matrix, offering a more detailed breakdown of the model's performance across various evaluation metrics. It provides a comprehensive summary of key metrics such as precision, recall, F1-score, and support for each class.

Precision measures the accuracy of positive predictions, indicating the proportion of correctly predicted instances among all instances predicted as positive. Recall, also known as sensitivity, quantifies the model's ability to capture all positive instances, representing the proportion of correctly predicted positive instances among all actual positive instances. F1-score, the harmonic mean of precision and recall, offers a balance between these two metrics, providing a single value that summarizes the model's performance. Additionally, the classification report includes the support metric, representing the number of occurrences of each class in the test dataset.

Classification Report:

	precision	recall	f1-score	support
Abnormal heartbeat	0.99	0.91	0.95	233
History of MI	0.95	0.95	0.95	172
MI Patients	0.97	1.00	0.99	239
Normal	0.96	0.99	0.98	284
accuracy			0.97	928
macro avg	0.97	0.97	0.97	928
weighted avg	0.97	0.97	0.97	928

Fig: 11 Classification Report of CardioNet Fusion Model

5.4 SALIENCY MAP

The saliency map highlights the important regions in the images processed by the models. These maps visually indicate which parts of the image contributed most to the model's prediction, aiding in interpretation.

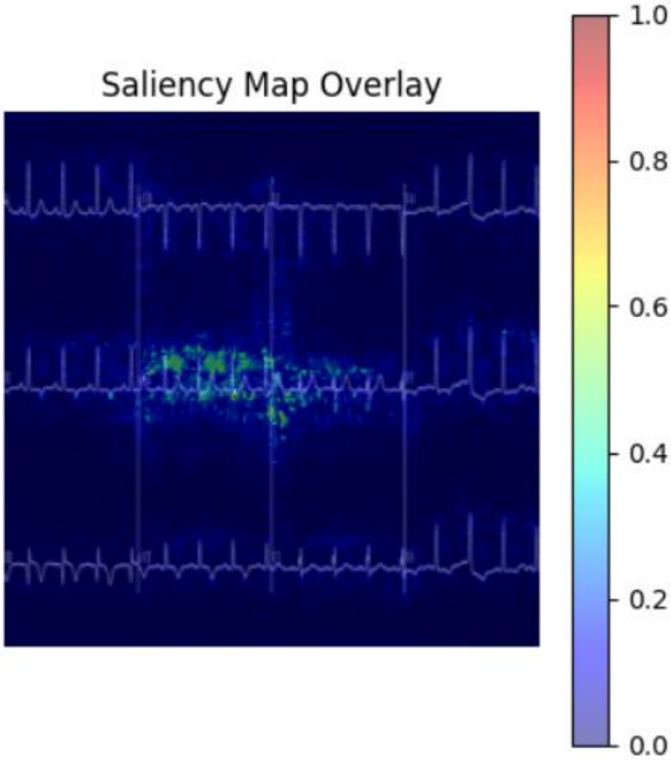

Fig: 12 Saliency map

5.5 WEB INTERFACE

The web interface allows users to upload images and receive predictions along with confidence scores from each model. Additionally, the interface displays the corresponding saliency map for each prediction, helping clinicians understand why a certain prediction was made. By visually correlating predictions with salient regions in the images, our interface facilitates deeper insights and validation of the model's decision-making process.

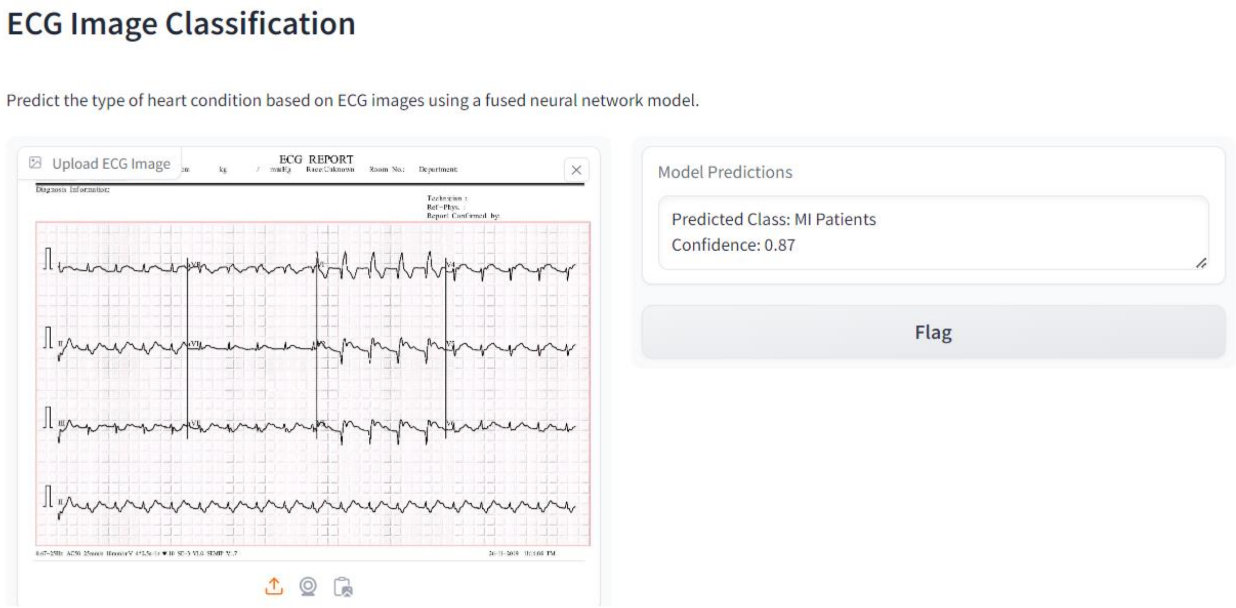

Fig: 13 Web Interface

CHAPTER 6

CONCLUSION

In conclusion, this project has explored the application of deep learning models for the classification of ECG images related to arrhythmia and myocardial infarction which serves as biomarkers for cardiotoxicity detection, culminating in the development of the Cardionet fusion model with a remarkable accuracy of 96.7%. The study highlights the potential of advanced computational techniques in early detection and monitoring of cardiac abnormalities, laying a foundation for more accurate tools in cardiovascular health assessment.

A web interface has been developed to provide easy access to the Cardionet fusion model, allowing individuals to assess their cardiac health remotely. This web interface serves as a valuable tool for users to gain insights into their cardiovascular health, promoting proactive management and early intervention strategies.

Moreover, the successful development and deployment of the web interface underscore the project's commitment to accessibility and user-friendliness in cardiovascular health management. By providing individuals with a convenient platform to assess their cardiac health remotely, the project not only empowers users to take proactive steps towards their well-being but also fosters a culture of preventive healthcare. This initiative marks a significant step forward in leveraging technology to democratize access to advanced cardiac monitoring tools, ultimately contributing to improved overall health outcomes on a broader scale.

CHAPTER 7

FUTURE WORKS

In future works, the integration of cardiac troponin levels alongside ECG data presents a promising avenue for enhancing the predictive capabilities of cardiac health monitoring systems. By incorporating cardiac troponin, a biomarker commonly associated with myocardial injury, into deep learning models, it may be possible to provide more comprehensive assessments of cardiac health, including the detection of subtle abnormalities indicative of early-stage cardiovascular diseases.

Additionally, the development of a wearable device capable of simultaneous ECG and cardiac troponin measurement offers a novel approach to continuous cardiac monitoring. Such a device could provide real-time insights into cardiac function and myocardial health, enabling early intervention and personalized treatment strategies for individuals at risk of cardiotoxicity. Integrating ECG and cardiac troponin measurements in a wearable device holds the potential to revolutionize remote cardiac monitoring, empowering individuals to proactively manage their cardiovascular health and improve clinical outcomes.

Furthermore, exploring the potential of federated learning techniques in the context of cardiac health monitoring presents an exciting direction for future research. Federated learning allows models to be trained across multiple decentralized devices while keeping data localized, thereby addressing privacy concerns associated with centralized data collection. By implementing federated learning, it becomes feasible to leverage diverse datasets from various sources, enhancing the robustness and generalizability of deep learning models for cardiac health assessment. This approach not only improves model performance but also ensures the inclusivity of diverse demographic groups, leading to more equitable healthcare solutions.

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