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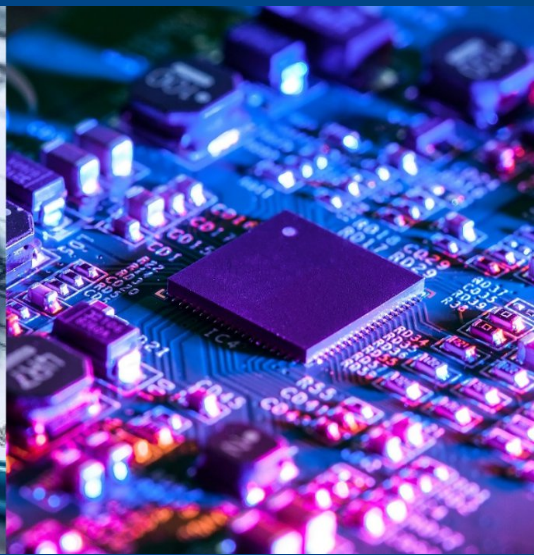

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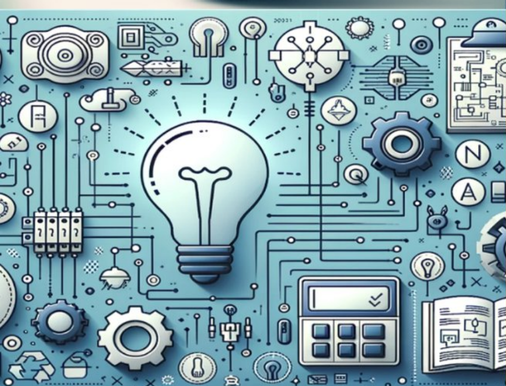

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An Enhanced Deep Learning Framework for Heart Disease Classification using Echocardiogram Images

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ABSTRACT: Heart disease remains one of the leading causes of deaths worldwide, and early detection is critical for effective treatment. Echocardiography is a widely used, non-invasive imaging technique to visualize the heart. We proposed a hybrid deep learning model that combines the VGG and InceptionNet for accurate and automated cardiac disease detection using echocardiogram images. By considering the VGG's feature extraction capabilities and InceptionNet's ability to efficiently capture features at multiple scales, the system will be trained and evaluated on a labeled echocardiogram dataset, and can also gain improved accuracy and robustness compared to using either architecture alone. The model is evaluated using Accuracy, Precision, F1-score, Recall and confusion matrix. This study focuses on the practical application of deep learning in medical image analysis for cardiac disease detection. The system enhances early diagnosis capabilities, contributing to reduced health risks and more informed clinical decision-making.

KEYWORDS: Echocardiography, VGGNet, InceptionNet, Hybrid CNN Model, Feature Extraction, Cardiovascular Disease.

I. INTRODUCTION

Heart disease is the most common disease in recent days according to the World Health Organization. In 2025, cardiovascular disease remains the leading cause of global deaths [1]. Globally around 32% of deaths occurred. This health issue is increasing with the age of 18 to 45 [2]. There is drastic increase in sudden cardiac deaths among the above mentioned age group people. The leading cause of drastic increase in the heart diseases among all aged people is the lifestyle-related risks such as obesity, high blood pressure, smoking, Rapid urbanization, sedentary lifestyles, poor dietary habits, and high stress are primary contributors. The diseases Angina, Cardiovascular, coronary artery and hypotensions are the collectively bear significant economic and societal burdens. By 2050, the absolute number of global deaths due to cardiovascular diseases (CVD) is projected to reach

35.6 million annually [3]. Early diagnosis of cardiovascular disease can lead to effective treatment which may help stop morbidity and mortality rates. There are different heart diagnosing methods are usually followed by doctors. The primary check up that doctor follows is to check heart rate, blood pressure, breathing and etc using stethoscope to detect abnormal heart sounds. Most commonly used heart disease diagnostic methods are Electrocardiography(ECG) [14], Echocardiography, Anginography. Electrocardiography and blood tests are used for Initial diagnosis, echocardiography is used for structural analysis and anginography is used for the conforming of blockages. Echocardiograms studies the size of the heart, how well it works, valve problems, and the enlargement of its chambers.

Ultrasound waves are used in echocardiography, a noninvasive imaging technique, to create images of the heart. Echocardio-graphy has vast benefits, but it also has dependency on professional interpretation with drawbacks, especially in places where access to qualified cardiologists is restricted. As a result, there is now more interest in using cutting-edge technology, such deep learning, to facilitate the sis of echocardiography pictures. A well known CNN design that has been quite successful in a variety of image identification applications, including medical imaging.

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The main goal of this study is the classification of four different heart disease types—angina, coronary artery disease (CAD), hypotension, and cardiovascular disease (CVD). The dataset is having 2404 echocardiogram images, evenly divided among the four diseases categories. No.of images for each disease are angina disease(606), cardiovascular disease(599), coronary artery disease(599), hypotension disease(601). Our model is evaluated using confusion matrix and classification report.

II. LITERATURE REVIEW

Many researchers did heart disease predictions using ML classification techniques. The ML classifiers used in this work have shown promising results in detecting the risk of CVD. There are many studies about the heart disease classification.

Deep learning, particularly convolutional neural networks (CNNs), revolutionized medical imaging analysis after the release of ImageNet in 2012 [4]. Another study reviews DNN applications in classification, detection, localization, and segmentation across various imaging modalities like X-Ray, MRI, and CT. While CNNs excel in image feature extraction, challenges such astraining time, data augmentation, and annotation remain. Future research focuses on enhancing DNN frameworks and advancing healthcare applications.

Recent advancements in heart disease classification have increasingly enabled deep learning and hybrid approaches to improve diagnostic accuracy and reliability. A number of recent studies (2023–2025) highlight the transition from traditional machine learning models to more sophisticated architectures that combine spatial, temporal, and explainable components [7].

In 2025, Eshetie Gizachew Addisu et al. [8] proposed a hybrid framework integrating VGG16 with classical machine learning classifiers such as SVM, Random Forest, and XGBoost, along with explainable AI techniques like LIME and SHAP. Their model achieved accuracy of 96.43%, proving that hybrid models can not only enhances predictive performance but also improves interpretability, which is crucial in medical decision-making. This work represents the growing importance of explainable AI in healthcare applications.

Similarly, Vivek Pandey et al. [9] (2024) introduced a multi-component architecture combining M2MASC, CNN-BiLSTM, and VGG16 as a feature extractor. Using a large-scale 12-lead ECG dataset, their model achieved 98.07% accuracy, outperform-ing traditional CNNs and standalone machine learning approaches. The including of BiLSTM allowed the model to capture temporal dependencies in ECG signals, where CNN and VGG16 contributed to spatial feature extraction, results in a highly robust classification system.

In another study, Spandana S et al. [10] (2023) developed a VGG16-based deep learning model for cardiac MRI data, achieving 96% accuracy. Their results shows that the proposed model outperformed not only other deep learning architectures like ResNet and Inception but also human experts in certain evaluation metrics such as precision, sensitivity, and F1-score. This shows the potential of deep learning systems to assist clinical expertise.

Focusing on echocardiogram data, Deepika Saningappala and N. Jaisankar (2025) [11] proposed a model combining InceptionV3 with a Multi-View Convolutional Neural Network (MVCNN). Their approach achieved an accuracy of 98.09%, effectively capturing both spatial and temporal features from echocardiogram videos. This study shows the effectiveness of multi-view learning in handling complex medical imaging data.

In a related work, Irem Sayin et al. (2024) [12] utilized a CNN combined with Inception-based feature extraction on ECG datasets, achieving 93.27% accuracy. Their outputs show that incorporating Inception modules enhances feature representation and improves classification performance compared to baseline CNN models.

Additionally, Deepika Saningappala (2023) [13] used InceptionV3 for echocardiogram video analysis, showing an accuracy of 96%. The study shows the model's ability to effectively detect various heart disease conditions through video-based feature extraction.Overall, the literature indicates a clear trend toward hybrid and deep learning-based approaches for heart disease classification. Models that integrate multiple architectures or combine spatial and temporal feature extraction techniques consistently achieve higher accuracy compared to traditional methods. Also, the incorporation of explainable AI and multi- is emerging as a best way to enhance both performance and trustworthiness.

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III. PROPOSED METHOD

In this study, a theoretical explanation of the deep learning technique is needed for understanding the methods. A convolution neural network's input constantly favors a certain type of image, and it uses filters to identify temporal and spatial aspects in images in addition to detecting properties like color, texture, and edges. CNN will use weight distribution algorithms with fewer parameters to cut down on computing time. There are filters and kernel sizes in each layer. The pooling layer helps distinguish the features separately by reducing the size of the feature map and generalizing characteristics that were extracted by earlier kernels following convolution.

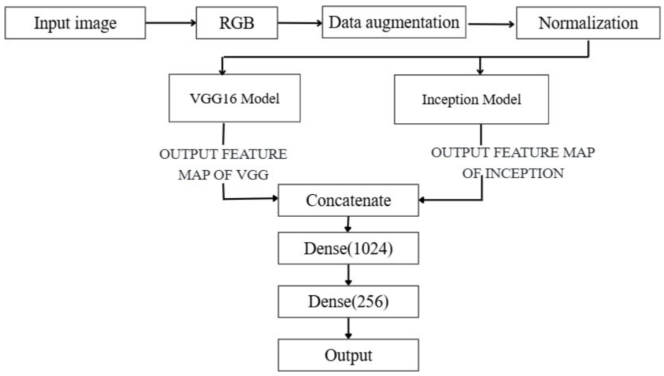

Fig. 1. Flow Chart.

This proposed model relies on deep Convolutional Neural Network (CNN) structure to capture and analyze complex features from input images. The network starts with an input layer that is intended to take in the 224 × 224-pixel image 3 color channels. A series of convolutional layers are then used to learn hierarchical feature representations. This hybrid model is the combination of vgg and inception models. The input image is resized to 224 x 224 pixels. The gray scale image is converted to rgb. The rgb images are now converted to the bgr images, as pretrained models expect specific preprocessing. The image undergoes data augmentation and preprocessing. As the data set is small dataset but the models are heavy models there is the requirement is huge data set. So, data augmentation is performed on the dataset. In data augmentation performs zoom, rotate and flip operations. Rotation is done about 15 degrees and horizontal flip operations are performed. During preprocessing mean subtraction normalization is performed on the image. Mean subtration normalization means to subtract the mean value of rbg in the each pixel of the image respectively. Then the image will be given to both vgg and inception individually. The output feature maps of both models are concatenate using concatenate layer. Here dense layer is used as the classifier. Softmax activation function is used to convert the output to probability. Final output represents the disease present in the echocardiogram image.

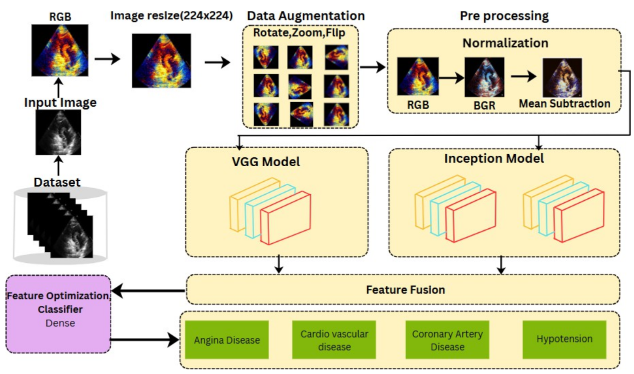

Fig. 2. Hybrid Model.

This work is aimed at enhancing the performance of deep learning in heart diseases classification for a better clinical decision.

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IV. EXPERIMENTAL RESULTS

Our research dataset includes a total of 2404 echocardiogram images and class labels namely Angina Disease, Cardiovascular Disease (CVD), coronary artery disease (CAD) Hypotension. We created histograms to see how our dataset is distributed. The histograms illustrate the distribution of images over each class. This is a visualization to check our dataset it should be balance and representable from each class.

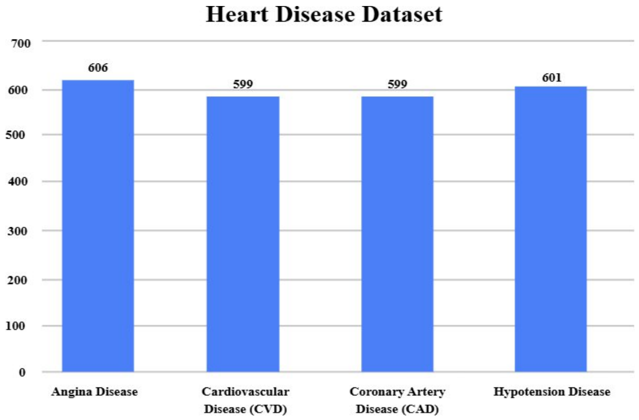

Fig. 3. Histogram showing no.of images in each class.

Then we split the data into three subsets: training, validation, and test sets, with a ratio of 70%, 12%, and 18% respectively. This experiment was run with Google colab's T4 GPU in Python. Python was used to train and deploy the model, with 100 epochs of training. T4 GPU enabled fast processing training, leading to better model performance and accuracy. The below sample echocardiogram images are from the dataset.

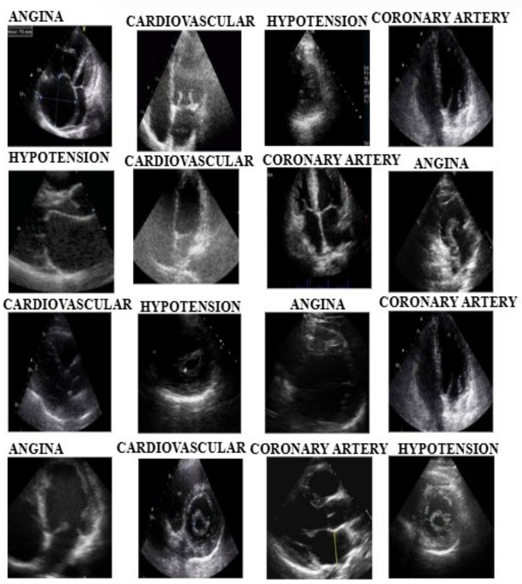

Fig. 4. Sample images from each class.

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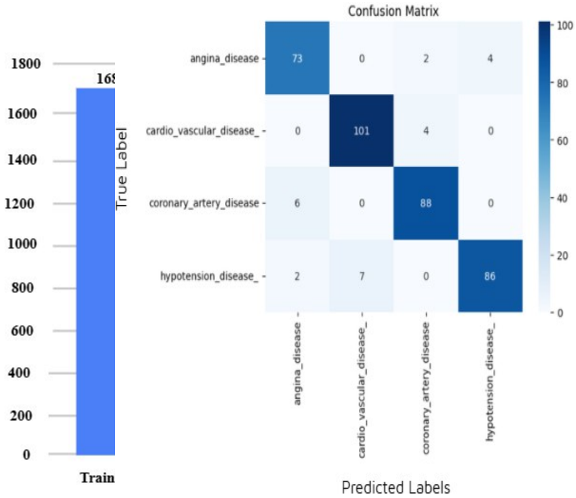

Fig. 5. Data split for training, validation, and test sets.

A. ***VGG16***

For the first experiment (VGG-16), we will make use of base VGG16 model [5] and we obtained an average accuracy of 93.17%. The training and validation accuracy over epochs were plotted. These plots help us to understand how the model did compare it's in previous epochs They allow us to see how quickly the model is learning and how well it generalizes to data that's outside of what was visible. During the experiments we have generated the confusion matrices. The confusion matrix gives you a detailed breakdown of the model's performance, and showshow many of each class label were correct vs. incorrect predictions.

B. ***InceptionNet***

In this experiment of InceptionNet model is used due to its computationally demanding nature. In this case InceptionNet leverages the small compact model with good accuracy balance. It was instantiated the InceptionNet model [6] with weights pre-trained on the ImageNet dataset.Training and Validation accuracy over epochs for InceptiontNet. Accuracy of this model for this dataset is 91.13%.

This confusion matrix was made for the InceptionNet model. The matrix is showing how many predictions fall into particular classes and what areas of the model are good at, and which needs to be improved.

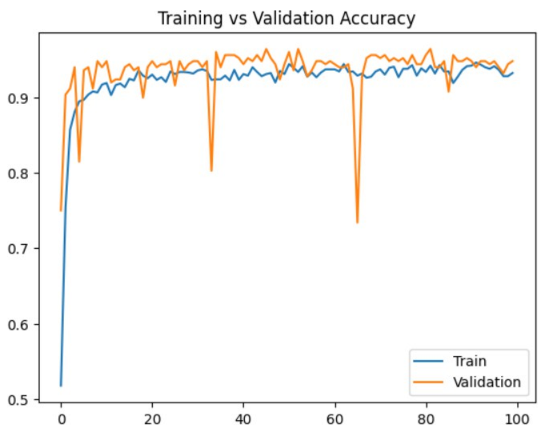

Fig. 6. Traning and Validation Accuracy(VGG16).

Fig. 7. Confusion matrix(VGG16).

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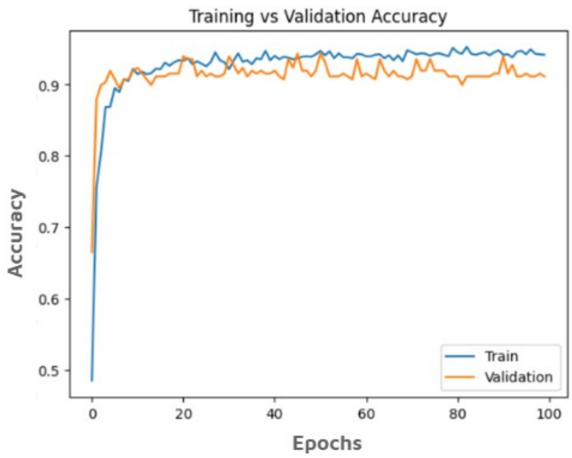

Fig. 8. Training and Validation Accuracy(InceptionNet).

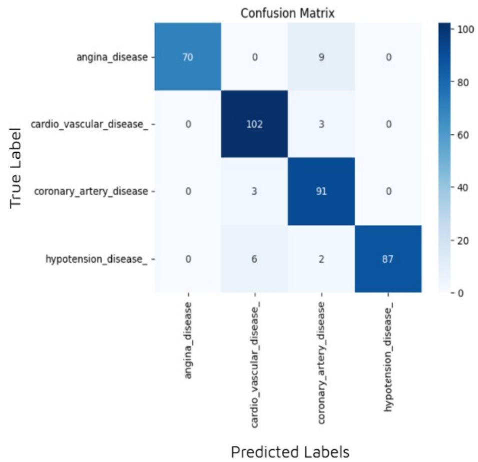

Fig.9. Confusion matrix(InceptionNet).

C. ***Proposed Model(Hybrid Model)***

The hybrid model provides the Average accuracy of 93.75%. This exceeded performance of the original base model.Similar to 1st 2nd experiment the training and validation accuracy over epochs were plotted.

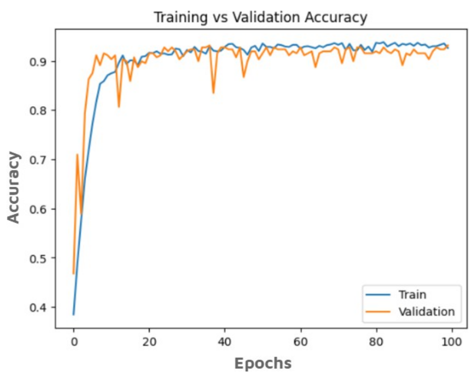

Fig. 10. Training and validation Accuracy(Hybrid Model).

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The confusion matrix gives you a detailed breakdown of the model's performance, and shows how many of each class label were correct vs. incorrect predictions.

V. RESULTS DISCUSSION

The performances in terms of the accuracy, precision, recall and F1-score was measured to evaluate our model. Precision is the proportion of true positive in all predicted as positives. Precision calculates how many of the correct changes are actually proper. Recall measures the all actual positive cases that exist, what proportion is captured. The F1-score score is the harmonic mean between precision and recall. where TP, TN, FP, and FN indicate True Positive, True Negative, False Positive, and False Negative.

$$\text{Precision} = \frac{TP}{TP + FP} \times 100\% \quad (1)$$

$$\text{Recall} = \frac{TP}{TP + FN} \times 100\% \quad (2)$$

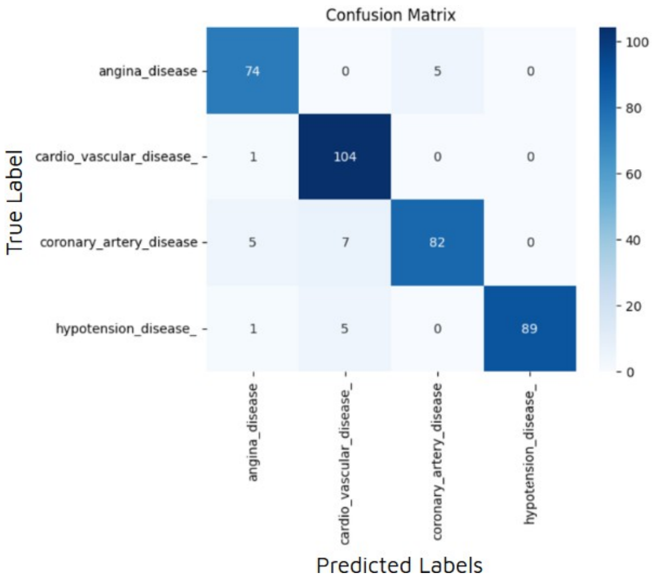

Fig. 11. Confusion matrix(Hybrid Model).

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \times 100\% \quad (3)$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \times 100\% \quad (4)$$

In test accuracy, VGG-16 scored 93.17%, InceptiontNet scored 91.13%, and our proposed method achieved the average accuracy at 93.75%. This proves how well our proposed method works, even with new data.

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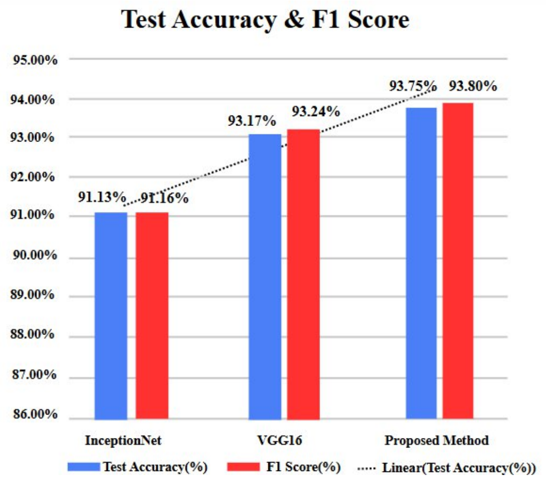

Fig. 12. Comparing different models(Inception, VGG, Proposed model).

The classification report shows the performance metrics of each disease class. The proposed method performed best when examined from the point of recall, marking highest average-recall for Angina Disease (at 100%), followed by VGG-16(94%) and InceptionNet(at 81%). For the CAD the Recall of our method is 90%; thus, less than VGG-16 (94%) and InceptionNet model which is about around at 94%. The proposed method performs exceptionally well in F1-Score. It gets a score of 93% in Angina Disease, which is equal to VGG-16 (93%) and slightly less for InceptionNet(90%). For CVD, 92%, matching inception and lesser than VGG-16 (96%) The most striking comparison is when applying the metric F1-Score to CAD, our method obtains a larger score than Inception (95% vs 89%) and even vgg is lesser with 94%. In all, our proposed method

performs better on many fronts. The model is very effective on all classes, in a way that it has the biggest F1-Scores for Angina and CAD while reaches also at highest recall values for Angina Disease , with perfect precision rate of 100% only reserved to Hypotension. The results demonstrate the effectiveness of our proposed method in medical condition classification and also its strength on robustness.

Experiment	Metrics	Angina	CVD	CAD	Hypotension
VGG 16	Precision	93%	93%	94%	100%
	Recall	94%	99%	94%	92%
	F1 Score	93%	96%	94%	96%
Inception	Precision	100%	86%	84%	100%
	Recall	81%	99%	94%	89%
	F1 Score	90%	92%	89%	94%
Proposed method	Precision	87%	88%	100%	100%
	Recall	100%	97%	90%	86%
	F1 Score	93%	92%	95%	92%

Fig. 13. Comparing (Inception, VGG, Proposed model) classification report includes precision, recall and f1 score.

The results from the experiment demonstrate that the proposed method outperforms both VGG-16 and InceptionNet in classifying heart diseases from Echo images. In this total summary, we use a dataset of 2404 echocardiogram images (Angina Disease, Cardiovascular Disease (CVD), coronary artery disease (CAD) and Hypotension). We used a well-known dataset from Kaggle and experimented with VGG-16, InceptionNet for evaluating our method [16]. Experimental results demonstrate the superiority of our proposed method over several conditions in terms precision, F1-Score and recall. It also exhibits the best performance in terms of F1-Scores for Angina and CAD, recall for Angina Disease and Hypotension.

VI. CONCLUSION

In our research we've studied the potentials of deep learning using VGG16 based models Its variants for classification heart disease from Echo-images. We can get our model to improve its performance and not overfit. Contribution to medical imaging and heart disease detection, our research contribution within the domain of Medical Imaging and Heart Disease Detection has few important things. It supports the efficacy of deep learning models, especially VGG16 in classifying various heart diseases correctly from echocardiogram images. In this work we give our perspective on how those hyperparameters dropout rate and momentum played the most relevant role in model performance. These results should guide future studies which aim to enhance deep learning models for medical image classification. The clinical validation of the developed models on actual data, to be sure that they can be more practically useful and reliable in real-world clinical applications.

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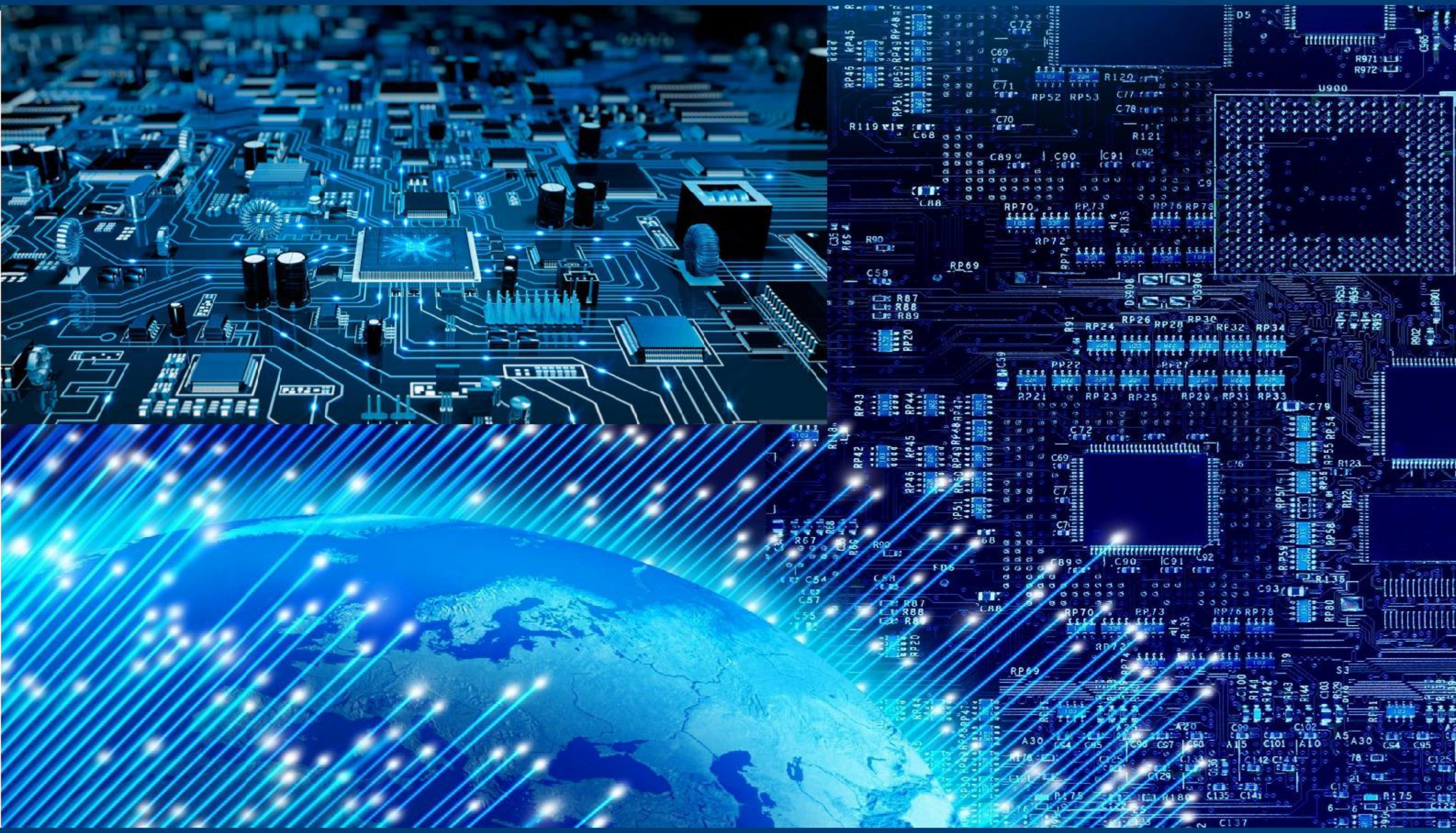

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