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CARDIOVASCULAR DISEASES DETECTION INECG IMAGES USING DEEP LEARNING METHODS

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***Abstract*—Heart diseases are the leading cause of death worldwide. So,detecting and identifying them earlier can save many lives.Electrocardiogram (ECG) is a common and inexpensive tool for measuring the electrical activity of the heart and is used to detect cardiovascular disease.In this paper, the power of deep learning techniques was used to predict the four major cardiac abnormalities: abnormal heartbeat, myocardial infarction, history of myocardial infarction, and normal person classes using the public ECG images dataset of cardiac patients. First, the preatrained models, namely SqueezeNet, AlexNet, proposed CNN and Xception were proposed for abnormality prediction.Second, these models were used as feature extraction tools for traditional machine learning algorithms, namely support vector machine, K-nearest neighbors, decision tree, random forest, and Na¨ıve Bayes. According to the experimental results, the performance metrics of the Xception model outperform the exciting works; it achieves 99.5% accuracy, 99.5% recall, 99.5% precision, and 99.5% F1 score. Moreover, when the Xception model is used for feature extraction, it achieves the best score of 99.8% using the RF and DT algorithms.**

***Index Terms*—Cardiovascular, deep learning, electrocardiogram (ECG) images, feature extraction, machine learning, transfer learning.**

I. Introduction

Heart diseases are the leading cause of death globally, claiming about a third of all lives each year. Most of these deaths are due to heart attacks. Early detection of cardiovascular issues is crucial for saving lives [1]. Various methods like electrocardiogram (ECG), echocardiography, and imagingtechniques are used to diagnose heart diseases [2],[3]. ECG, in particular, is common and affordable. It measures the heart's electrical activity and helps identify heart-related problems [4]. However, manual interpretation of ECG results can be prone to errors and time-consuming.[5]

Artificial intelligence (AI), especially machine learning and deep learning, offers promising solutions to improve heart disease diagnosis accuracy and efficiency[6]-[10]. These AI methods require identifying relevant features from the data. Feature extraction involves reducing the number of features while retaining essential information [11],[12]. Feature extraction involves transforming the original input features into a new set of features that capture the essential information present in the input data but in a lower-dimensional space. This process aims to condense the data while retaining as much relevant information as possible. Principal component analysis is a popular method for this [13],[14]. Feature selection, on the other hand, focuses on removing irrelevant or redundant features from the data. There are different methods for feature selection, including unsupervised and supervised approaches like filter, wrapper, and embedded methods[11],[12]. In a nutshell, AI can enhance heart disease diagnosis by automating processes and improving accuracy, making it a valuable tool in healthcare.

Researchers have been using different machine learning methods to predict heart diseases. They've tested various algorithms like decision trees, Na¨ıve Bayes, K-nearest neighbors, and neural networks on heart disease datasets[15]. One study found that decision trees had the highest accuracy at 89%. Another study looked at how selecting the right features from the data affects prediction accuracy [16]. They found that with a method called backward feature selection, they achieved the highest accuracy of 88.52% using decision trees. In other research, machine learning algorithms like Na¨ıve Bayes were used to detect heart disease, achieving an accuracy of 71.6%[17]. Researchers also compared different algorithms like neural networks and support vector machines for predicting heart diseases using ultrasound images and ECG signals. They found that combining features from both types of data gave the best accuracy, with support vector machines performing the best at 89.51%. Deep learning, a type of machine learning, automatically finds important features from data without needing separate feature selection[18]. It uses models called neural networks with many layers. One popular method, called convolutional neural networks, has been successful in classifying images. Researchers have also used pretrained deep learning models, like SqueezeNet[19] and AlexNet[20], for heart disease classification. These models can extract features from data and improve traditional machine learning methods' performance in predicting heart diseases.

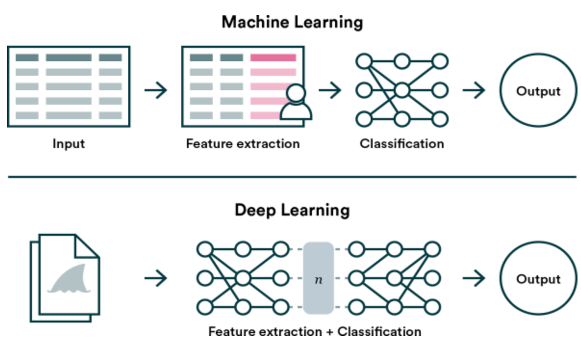

Fig. 1. Concept of machine learning and deep learning.

II. LITERATURE REVIEW

Numerous studies ([21]–[24]) have explored the automated prediction of cardiovascular diseases using both machine learning and deep learning techniques, leveraging ECG data in digital or image formats as representations.

[25] R. Bharti, A. Khamparia, M. Shabaz, G. Dhiman, S. Pande, and P. Singh, "Prediction of heart disease using a combination of machine learning and deep learning," Comput. Intell. Neurosci., vol. 2021, 2021, Art. no. 8387680. [Online]. Available: https://doi.org/10.1155/2021/ 8387680.
Bharti et al. compared machine learning and deep learning methods using a heart disease dataset. The deep learning method achieved the highest accuracy rate of 94.2%. Their deep learning model had three layers: the first with 128 neurons, followed by a dropout layer, the second with 64 neurons and another dropout layer, and the third with 32 neurons.Meanwhile, machine learning methods, when combined with feature selection and outlier detection, achieved lower accuracy rates: Random Forest (RF) had 80.3%, Logistic Regression (LR) had 83.31%, K-Nearest Neighbors (K-NN) had 84.86%, Support Vector Machine (SVM) had 83.29%, Decision Tree (DT) had 82.33%, and XGBoost had 71.4%.

[26]S. Kiranyaz, T. Ince, and M. Gabbouj, "Real-time patient-specific ECG classification by 1-D convolutional neural networks," IEEE Trans. Biomed.Eng., vol. 63, no. 3, pp. 664–675, Mar. 2016. [Online]. Available: https://doi.org/10.1109/TBME.2015.2468589.
Kiranyaz developed a convolutional neural network (CNN) with three layers specifically designed for analyzing long streams of ECG data from the MIT-BIH arrhythmia dataset. Their CNN achieved impressive accuracy rates of 99% for identifying ventricular ectopic beats and 97.6% for identifying supraventricular ectopic beats.

[27]A. H. Khan, M. Hussain, and M. K. Malik, "Cardiac disorder classification by electrocardiogram sensing using deep neural network," Complexity,vol. 2021, 2021, Art. no. 5512243. [Online]. Available:https://doi.org/10.1155/2021/5512243.
Khan employed a transfer learning approach using a pretrained model called single shot detector (SSD)-MobileNet-v2 to detect cardiovascular diseases from ECG images. Their goal was to predict four major heart abnormalities: abnormal heartbeat, MI, history of MI, and normal heart condition. To prepare the data, they adjusted the image sizes and labeled the 12 leads of each ECG image. SSD, a method for object detection, was utilized to classify and locate abnormalities in one step. The dataset was divided into 80% for training and 20% for testing. During training, they used a batch size of 24, 200,000 iterations, and a learning rate of 0.0002. The training process took about four days to complete. Their model achieved impressive precision, particularly for detecting MI, with a precision rate of 98.3%.

[28]T. Rahman et al., "COV-ECGNET: COVID-19 detection using ECG trace images with deep convolutional neural network," 2021, arXiv:2106.00436.
Rahman proposed a deep convolutional neural network (CNN) transfer learning approach to predict both COVID-19 and four major cardiac abnormalities using ECG images. Their dataset contained five classes: COVID-19, abnormal heartbeat (AH), myocardial infarction (MI), history of MI (H. MI), and normal person (NP). They experimented with six different pretrained deep CNN models, including ResNet18, ResNet50, ResNet101, DenseNet201, Inception-V3, and MobileNet-v2 for classification. To prepare the ECG images for analysis, they applied preprocessing steps such as gamma correction, image resizing, and z-score normalization. DenseNet201 performed the best among the models for two-class classification (COVID-19 vs. normal) and three-class classification (COVID-

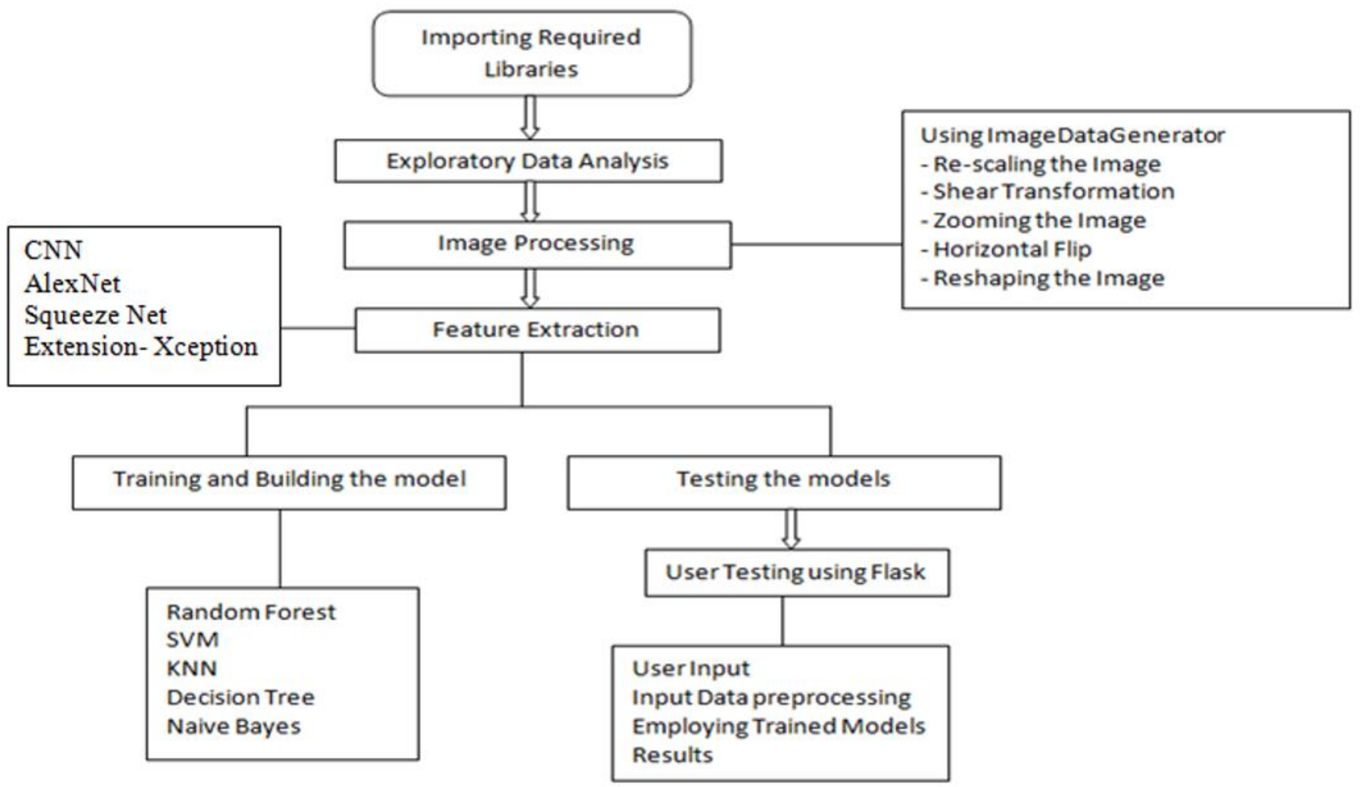

Fig. 2. Block diagram of the proposed methodology for Classification of Cardiovascular disease

19, normal, and other cardiac abnormalities) with accuracy rates of 99.1% and 97.36%, respectively. For the five-class classification, Inception-V3 achieved the highest accuracy rate of 97.83%.

[29]R. Avanzato and F. Beritelli, “Automatic ECG diagnosis using convolutional neural network,” Electronics, vol. 9, no. 6, 2020, Art. no. 951. [Online]. Available: https://doi.org/10.3390/electronics9060951.
Avanzato and Beritelli introduced a deep convolutional neural network (CNN) designed for detecting three classes of cardiac abnormalities using ECG signals from the MIT-BIH arrhythmia dataset. Their CNN architecture comprised four 1-D convolutional layers, each followed by a batch normalization layer, rectifier linear unit (ReLU) activation function, and max-pooling layer with a filter size of 4. The first convolutional layer used a filter size of 80, while the subsequent layers utilized a filter size of 4. Unlike traditional CNN architectures, their model didn’t include fully connected layers for classification. Instead, it employed an average pooling layer followed by a softmax layer for classification. Their model achieved an impressive accuracy rate of 98.33% in classifying cardiac abnormalities.

III. METHODOLOGY

A. *Convolutional Neural Networks (CNN)*

Convolutional Neural Networks (CNNs) are a specialized form of deep artificial neural networks designed primarily for image classification and processing tasks. Their architecture is characterized by neurons arranged in three dimensions—height, width, and depth (channel)—making them particularly adept at capturing spatial hierarchies and learning intricate patterns within images. CNNs consist of convolutional layers, where input data is convolved with filters or kernels to extract relevant features, and activation functions like ReLU introduce non-linearity to enhance representation learning. Pooling layers, such as max-pooling, downsample feature maps to reduce computational complexity while retaining essential information. Fully connected layers integrate these features for high-level abstraction and classification, with the final output layer typically employing activation functions like softmax to generate probability distributions across classes. Through their sophisticated architecture and efficient feature extraction capabilities, CNNs have revolutionized various domains, including computer vision and medical imaging, enabling researchers and practitioners to tackle complex tasks with precision and scalability.

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B. *Pretrained Deep Learning Models*

Transfer learning and feature extraction exploit the capabilities of pretrained deep neural networks like SqueezeNet and AlexNet, even on a single CPU, for various tasks. Transfer learning involves replacing the final layers of a pretrained network with new ones to adapt to specific features of a new dataset, fine-tuning the model with tailored parameters, and evaluating its performance on a separate test set, benefiting from the extensive learning on vast image datasets. Feature extraction utilizes the pretrained networks to extract learned features, saving time and effort on training. These extracted features are then employed to train traditional machine learning classifiers such as Support Vector Machines (SVM), k-Nearest Neighbors (K-NN), Decision Trees (DT), Random Forests (RF), and Naive Bayes (NB), enhancing performance without additional training. Leveraging pretrained networks accelerates model development, streamlines feature extraction, and enhances performance across various tasks in machine learning and computer vision domains.

1) *SqueezeNet:*

- Purpose: The architecture is designed to be efficient during inference on resource-constrained devices. This means it aims to perform tasks like processing and making predictions based on input data (e.g., images or videos) quickly and effectively, using minimal computational resources.

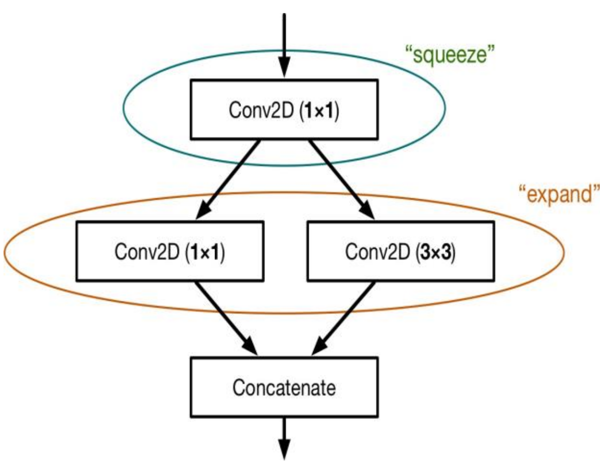

Fig. 3. SqueezeNet architecture

- Key Features: Utilizes 1x1 convolutions: These are convolution operations with a kernel size of 1x1. This technique helps in reducing the dimensionality of the input, allowing for depth-wise manipulation without the computational complexity of larger convolutions. It's effective for refining features and channel-wise interactions. Global average pooling: Instead of flattening the feature maps into a long vector, which is typical in many convolutional networks, global average pooling directly summarizes the spatial dimensions (height and width) of each feature map to a single number by taking the average of all elements. This significantly reduces the number of parameters and computational load in the network.

2) *AlexNet:*

- Purpose: The model being described was one of the first to apply deep learning effectively to image classification, which involves assigning a label to an image from a fixed set of categories based on its visual content. This was a pioneering effort that significantly advanced the application of deep learning in practical scenarios.

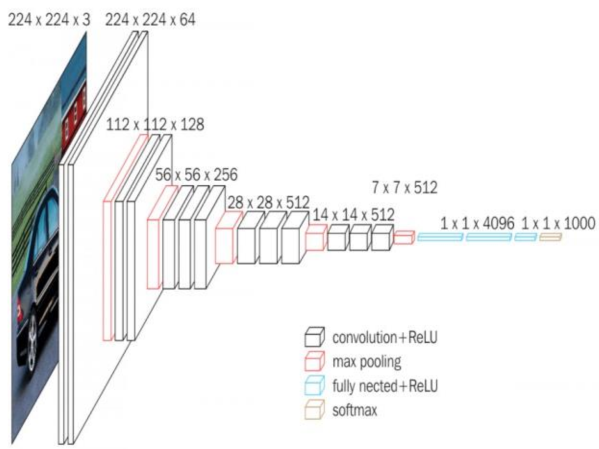

Fig. 4. AlexNet architecture

- Key Features: Introduced ReLU activation functions: ReLU (Rectified Linear Unit) is an activation function used in neural networks that allows the model to handle non-linear data with better efficiency and effectiveness. It is defined as the positive part of its argument, where $f(x) = \max(0,x)$, and helps with faster convergence and alleviating problems like the vanishing gradient.
- Dropout regularization: This is a technique used to prevent overfitting in neural networks. During training, some number of layer outputs are randomly ignored or "dropped out." This increases the robustness of the model as it cannot rely on the presence of particular features.
- Data augmentation techniques: These are methods used to increase the diversity of data available for training models without actually collecting new data. This involves applying a series of random transformations to training images, such as rotations, scaling, and flips, which helps improve the model's ability to generalize.

3) *CNN Model:*

- The proposed CNN architecture is designed for classifying cardiac abnormalities from ECG images. It features a dual-branch structure:
- Stack Branch: Composed of three stacked 2-D convolutional layers, each followed by a leakyReLU activation (with a slight slope for negative inputs to

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prevent neuron death), batch normalization (for faster training and improved accuracy), and a max-pooling layer (to reduce spatial dimensions and computational demands). The convolutional layers increase in filter count across the layers from 64 to 224, culminating in a reduced output size of 2x2x224.

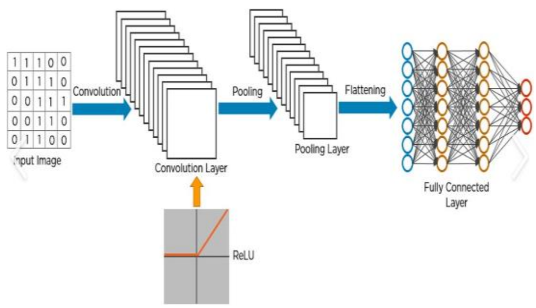

Fig. 5. CNN architecture

- Full Branch: Begins with a fully connected layer with 16 neurons, aimed at processing global features, followed by a leakyReLU, batch normalization, and a dropout layer to combat overfitting. Two additional convolutional layers enhance feature extraction, which are then concatenated to further blend the features. A final dropoutlayer minimizes overfitting. Both branches combine their outputs into a single feature map, which is then processed through a 1x1 convolution to reduce depth and manage complexity, followed by a large fully connected layer with 512 neurons to bolster the classification task. The model concludes with a softmax layer that determines the class probabilities for the four targeted cardiac conditions. This model is trained and tested on preprocessed ECG images, emphasizing efficiency and robust classification.

4) Proposed model - Xception: The Xception architecture is designed to enhance the efficiency and effectiveness of convolutional neural networks through a strategic use of depthwise separable convolutions.

- Input Layer:The model typically starts with an input layer that matches the size of the dataset images. For instance, in tasks involving ImageNet, the input size would be 299x299 pixels with 3 channels (RGB).
- Entry Flow: The entry flow of the Xception model begins with two initial convolutional layers which are standard convolutions, intended to start the feature extraction process. These layers are followed by a series of modules that use separable convolutions with increasing depth. Each module in the entry flow doubles the number of filters while reducing the spatial dimensions, usually through max-pooling, to compress the input while deepening the feature maps.
- Middle Flow: This section consists of eight identical blocks, each containing depthwise separable convolutions. The middle flow acts as the core of the network, where most of the processing happens. Each block has a residual connection that bypasses the separable convolutions, similar to the identity connections in ResNet. These connections help in avoiding the vanishing gradient problem during training, allowing deeper networks to learn effectively.
- Exit Flow: In the exit flow, the network concludes its feature processing with additional separable convolutions that further transform the feature maps. The exit flow typically includes some final downsampling to prepare the network for the classification task. The exit flow ends with a global average pooling layer which reduces each feature map to a single number by taking the average of all its values, effectively summarizing the output of the convolutional base into a fixed-size output.

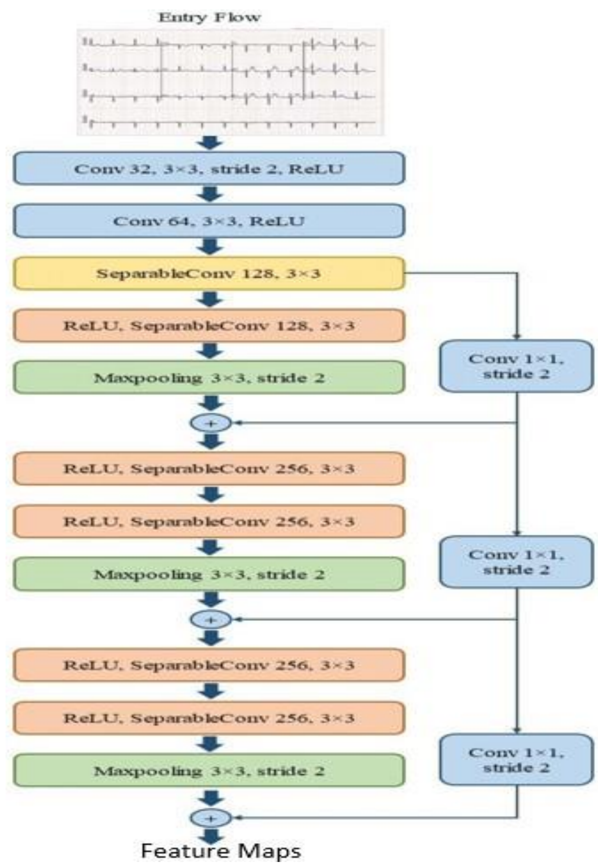

Fig. 6. Xception architecture

- Fully Connected Layer: After the global average pooling, the network transitions to one or more fully connected layers. These layers are designed to perform the high-level reasoning in the network. The last of these layers is often followed by a softmax activation function if the task is classification, which provides the probabilities of the input belonging to each class.
- Residual Connections: Throughout the middle and sometimes in the entry and exit flows, residual connections are

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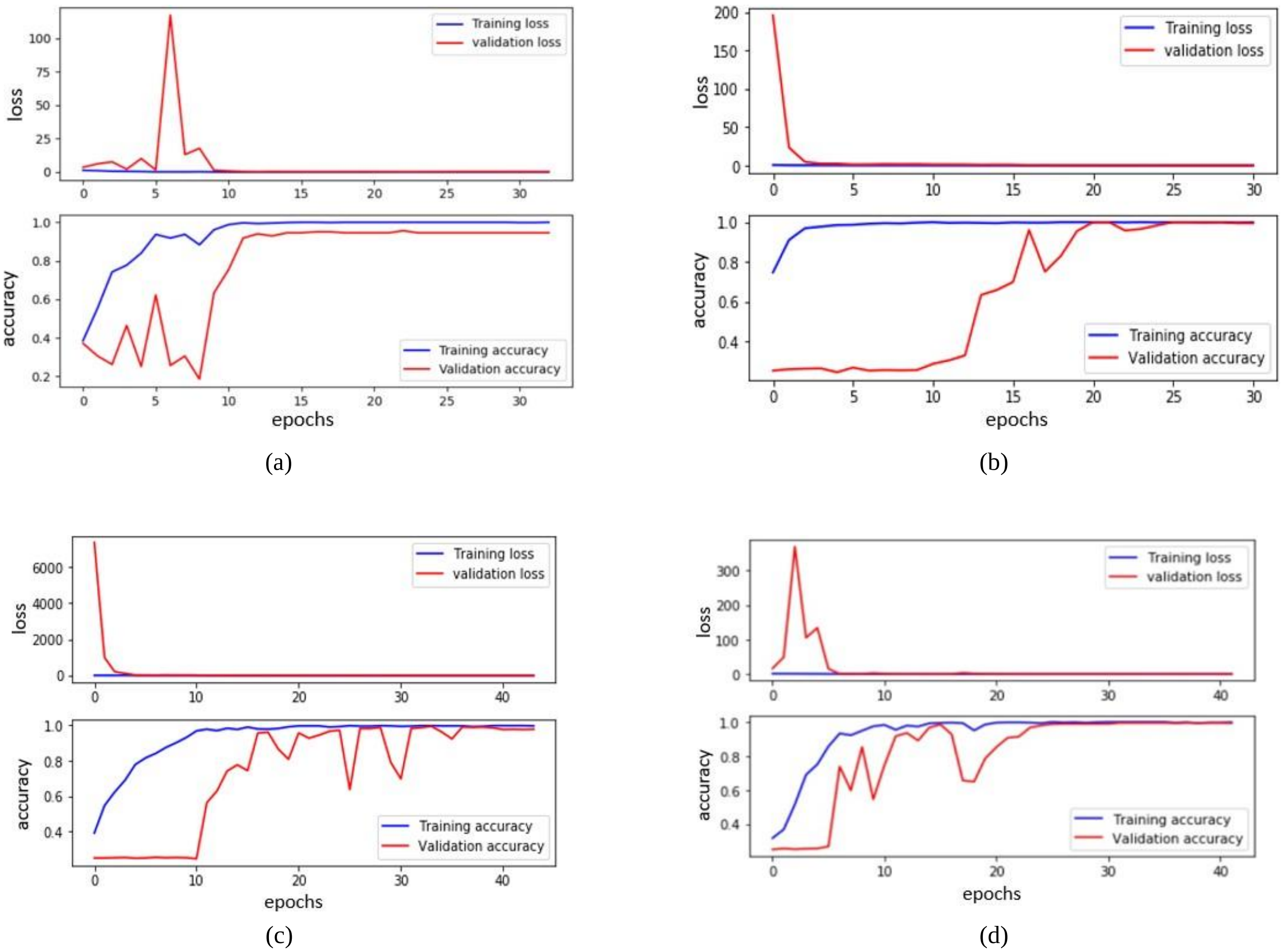

Fig. 7. Training Progress of (a)SqueezeNet, (b)AlexNet, (c)proposed CNN and (d)Xception model

employed. These connections help to propagate gradients through deep network architectures without much loss in signal, making training deeper networks feasible and more efficient.

After extracting features using the base Xception model, several layers are added to tailor the model for a specific classification problem with four classes:

- Global Average Pooling 2D: A global average pooling layer is applied to the output of the base model. This layer reduces each feature map to a single average value, diminishing the model's parameter count and computational complexity, and helps to minimize overfitting.
- Dense Layer: A fully connected dense layer with 512 neurons and ReLU activation provides the ability to learn high-level features from the pooled feature maps.
- Dropout: A dropout layer with a rate of 0.3 follows the dense layer to reduce overfitting by randomly setting a fraction of input units to 0 during training.
- Output Layer: The final layer is a dense layer with four neurons, corresponding to the four classes in the dataset. It uses a softmax activation function to output the probability distribution across the four classes.

IV. Results and Analysis

Accuracy, precision, reacall and F1 score were used for performance analysis which are based on confusion matrix.

TABLE I
PERFORMANCE METRICES

Filter Size	Measures	Defined as
1	Accuracy	(TP+TN)/(TP+FP+FN+TN)
2	Recall	TP/(TP+FN)
3	Precision	TP/(TP+FP)
4	F1 Score	(2*Recall*Precision)/(Recall+Precision)

Where accuracy is defined as the proportion of correct predictions made by the model compared to the total number of predictions made. Recall represents the fraction of actual positive cases that the model correctly identifies as positive out of all actual positive cases. Precision expresses the ratio of true

TABLE II
PERFORMANCE MEASUREMENTS FOR MACHINE LEARNING ALGORITHMS THAT USE PRETRAINED NETWORKS SQUEEZENET, ALEXNET, PROPOSED CNN AND XCEPTION AS FEATURES EXTRACTOR APPLIED ON ECG IMAGES DATASET

Pretrained Network	Algorithm	Accuracy	Precision	Recall	F1 score
Squeeze Net	-	0.973	0.966	0.942	0.953
AlexNet	-	0.985	0.965	0.984	0.974
CNN	-	0.943	0.947	0.942	0.944
Xception	-	0.995	0.995	0.995	0.995
SqueezeNet	RF	0.998	0.998	0.998	0.998
	SVM	0.346	0.305	0.346	0.324
	KNN	0.927	0.928	0.927	0.927
	DT	0.994	0.994	0.994	0.994
	NB	0.525	0.504	0.525	0.514
AlexNet	RF	0.989	0.989	0.989	0.989
	SVM	0.317	0.257	0.317	0.283
	KNN	0.861	0.865	0.861	0.862
	DT	0.968	0.974	0.964	0.968
	NB	0.420	0.513	0.420	0.461
CNN	RF	0.978	0.984	0.984	0.984
	SVM	0.370	0.232	0.370	0.285
	KNN	0.858	0.862	0.858	0.859
	DT	0.991	0.991	0.991	0.991
	NB	0.927	0.928	0.927	0.927
Xception	RF	0.998	0.998	0.998	0.998
	SVM	0.459	0.421	0.459	0.439
	KNN	0.896	0.899	0.896	0.897
	DT	0.998	0.998	0.998	0.998
	NB	0.944	0.921	0.954	0.937

positive predictions in relation to the total number of positive predictions made by the model. The F1 score is a harmonic mean of precision and recall, providing a single metric that balances both the consequences of false positives and false negatives in evaluating a model's accuracy.

A. Results of Pretrained deep neural network models

The pretrained models SqueezeNet, AlexNet, proposed CNN Model and Xception were used for classification purpose. Firstly, these models were trained using the ECG images in the dataset for classifying the images as 4 classes. These results were obtained from the experimental evaluation of the models on the ECG images dataset of cardiac patients. The graphical representations of the training outcomes from the four Deep Learning models analyzed in this study were presented in Figure 5, corresponding to the Squeeze Net, Alex Net, proposed CNN model, Xception respectively.

By observing these models'training loss and training accuracy, Xception model achieved the significant performance that is lowest training loss and highest accuracy rate when compared to the remaining neural network models.

B. Results of Pretrained Deep Learning Models As a Feature Extractor

After performing the training on pretrained network models, these models were utilized as feature extraction tools. Deep learning techniques enable us to extract image features without retraining the entire network. This involves computing the activations of the network through forward propagation up to specific feature layers.

These extracted features were then used to train various machine learning algorithms, including Support Vector machine (SVM), k-nearest neighbors(KNN), Decision Tree (DT), Random Forest (RF), and Naive Bayes (NB). Table III presents the performance measures obtained from this process and also graphical reprsentation of these performace measures is shown in fig.6. Notably, the RF and DT algorithms achieved the highest success rate of 99.8% for accuracy, recall, precision, and F1-score when our proposed Xeption model was used as the feature extractor. Although the extracted feature size of our proposed Xceptioon model is the smallest, it achieved the best results on all performance measures, as shown in table. Despite having the smallest extracted feature size, our proposed Xception model yielded the best results across all

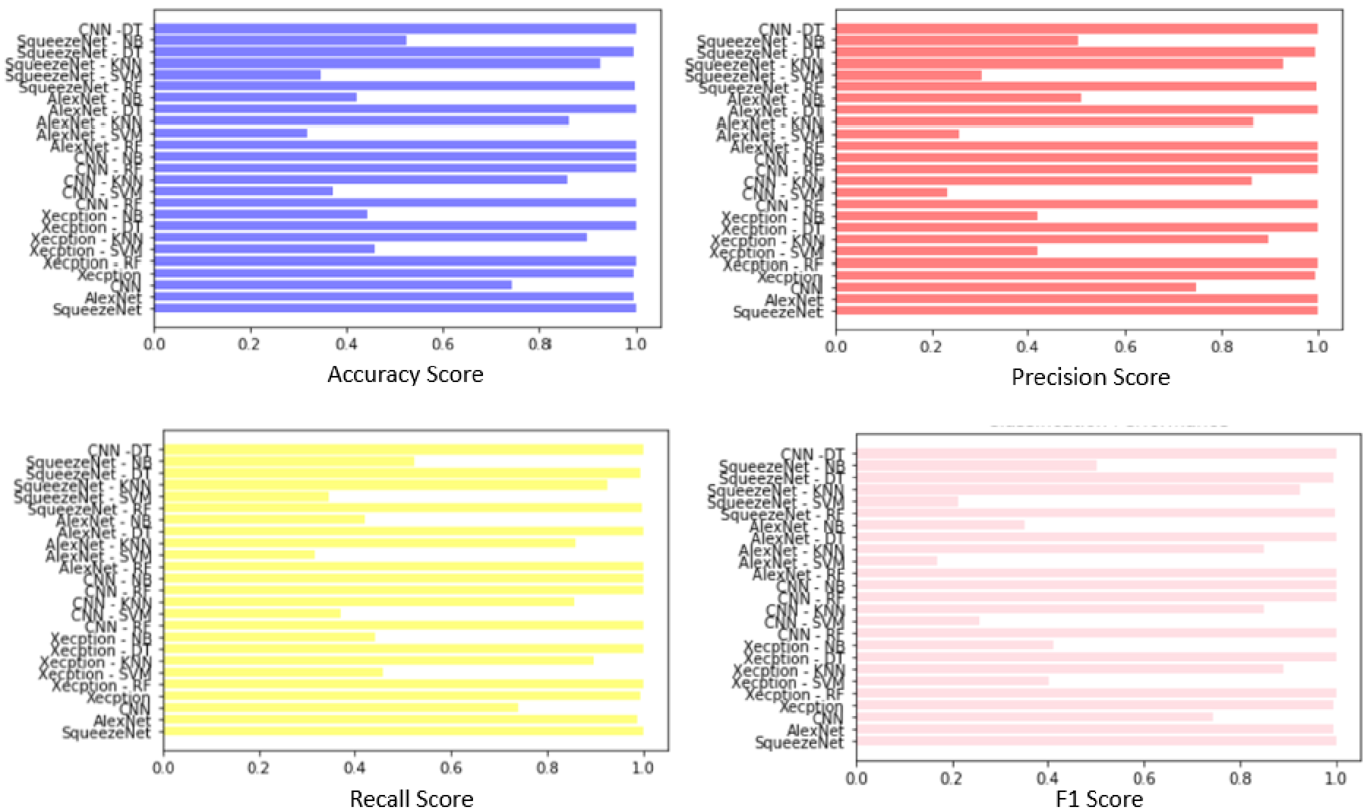

Fig. 8. Graphical visualization of Performances metrices of pretrained models

performance measures, indicating its capability to learn key features of the ECG images dataset.

Overall, our proposed model not only achieves superior accuracy rates but also incurs lower computational costs compared to existing approaches.

V. Conclusion

This article has highlighted the effectiveness of deep learning models, namely SqueezeNet, AlexNet, proposed CNN Model and Xception classifying four major cardiac abnormalities: AH, MI, H. MI, and NP, using a dataset of ECG images from cardiac patients. The experimental results demonstrate that our Xception model achieves significant success in cardiovascular disease classification and can also serve as a feature extraction tool for traditional machine learning classifiers. Consequently, our Xception model can assist clinicians in detecting cardiac diseases from ECG images, potentially replacing manual processes prone to inaccuracy and time inefficiency.

Looking ahead, we plan to fine-tune our Xception model's settings for even better performance. We also aim to use our model to predict different health problems beyond just heart issues. Since our model is not overly complicated, it might be useful in sorting and identifying things in the Industrial Internet of Things world. This opens up an exciting area for more exploration.

References

[1] World Health Organization (WHO), “Cardiovascular diseases,” Jun. 11,2021. Accessed: Dec. 27, 2021. [Online]. Available: https://www.who. int/health-topics/cardiovascular-diseases

[2] Jyoti Islam and Yanqing Zhang on “Brain MRI analysis for Alzheimer’s disease diagnosis using an ensemble system of deep convolutional neural networks”. Islamand Zhang Brain Inf. (2018) 5:2.

[3] M. Swathy and K. Saruladha, “A comparative study of classification and prediction of cardio-vascular diseases (CVD) using machine learning and deep learning techniques,” ICT Exp., to be published, 2021. [Online]. Available: https://doi.org/10.1016/j.icte.2021.08.021

[4] R. R. Lopes et al., “Improving electrocardiogram-based detection of rare genetic heart disease using transfer learning: An application to phospholamban p.Arg14del mutation carriers,” Comput. Biol. Med., vol. 131, 2021, Art. no. 104262. [Online]. Available: https://doi.org/10.1016/j.compbiomed.2021.104262

[5] R. J. Martis, U. R. Acharya, and H. Adeli, “Current methods in electrocardiogram characterization,” Comput. Biol. Med., vol. 48, pp. 133–149, 2014. [Online]. Available: https://doi.org/10.1016/j.compbiomed.2014.02.012

[6] A. Rath, D. Mishra, G. Panda, and S. C. Satapathy, “Heart disease detection using deep learning methods from imbalanced ECG samples,” Biomed. Signal Process. Control, vol. 68, 2021, Art. no. 102820. [Online]. Available: https://doi.org/10.1016/j.bspc.2021.102820.

[7] . Minchole´ and B. Rodriguez, “Artificial intelligence for the electrocardiogram,” Nature Med., vol. 25, no. 1, pp. 22–23, 2019. [Online]. Available: https://doi.org/10.1038/s41591-018-0306-1

[8] A. Isin and S. Ozdalili, "Cardiac arrhythmia detection using deep learning," Procedia Comput. Sci., vol. 120, pp. 268–275, 2017. [Online]. Available: https://doi.org/10.1016/j.procs.2017.11.238

[9] H. Bleijendaal et al., "Computer versus cardiologist: Is a machine learning algorithm able to outperform an expert in diagnosing phospholamban (PLN) p.Arg14del mutation on ECG?," Heart Rhythm, vol. 18, no. 1, pp. 79–87, 2020. [Online]. Available: https://doi.org/10.1016/j.hrthm.2020.08.021

[10] U. R. Acharya, H. Fujita, O. S. Lih, M. Adam, J. H. Tan, and *C.* K. Chua,"Automated detection of coronary artery disease using different durations of ECG segments with convolutional neural network,"Knowl.-Based Syst.,vol. 132, pp. 62–71, 2017. [Online].Available:https://doi.org/10.1016/j.knosys.2017.06.003

[11] M. Kantardzic,Data Mining: Concepts, Models, Methods, and Algorithms,3rd ed. Hoboken, NJ, USA: Wiley, 2020.

[12] S. Garc´ıa, J. Luengo, and F. Herrera, Data Preprocessing in Data Mining, 1st ed. Berlin, Germany: Springer, 2015.

[13] G. Dougherty, Pattern Recognition and Classification: An Introduction.Berlin, Germany: Springer, 2013.

[14] A. Subasi, Practical Machine Learning for Data Analysis Using Python.Cambridge, MA, USA: Academic, 2020.

[15] J. Soni, U. Ansari, D. Sharma, and S. Soni, "Predictive data mining for medical diagnosis: An overview of heart disease prediction," Int. J.Comput. Appl., vol. 17, no. 8, pp. 43–48, 2011.

[16] K. Dissanayake and M. G. Md Johar, "Comparative study on heart disease prediction using feature selection techniques on classification algorithms,"Appl. Comput. Intell. Soft Comput., vol. 2021, 2021, Art.no.5581806.[Online]. Available: https://doi.org/10.1155/2021/5581806

[17] A. H. Gonsalves, F. Thabtah, R. M. A. Mohammad, and G. Singh, "Prediction of coronary heart disease using machine learning: An experimental analysis," in Proc. 3rd Int. Conf. Deep Learn. Technol., 2019, pp. 51–56. [Online]. Available: https://doi.org/10.1145/3342999.3343015

[18] T. Ozcan, "A new composite approach for COVID-19 detection in X-ray images," Appl. Soft Comput., vol. 111, 2021, Art. no. 107669. [Online]. Available: https://doi.org/10.1016/j.aso

[19] F. N. Iandola, S. Han, M. W. Moskewicz, K. Ashraf, W. J. Dally, and K.Keutzer, "SqueezeNet: Alexnet-level accuracy with 50x fewer parameters and¡ 0.5 MB model size," 2016, arXiv:1602.07360.

[20] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," Adv. Neural Inf. Process. Syst.,vol. 25, pp. 1097–1105, 2012.

[21] C. Potes, P. Saman, A. Rahman, and B. Conroy, "Ensemble of feature-based and deep learning-based classifiers for detection of abnormal heart sounds," in Proc. Comput. Cardiol. Conf., 2016, pp. 621–624.

[22] A. Nannavecchia, F. Girardi, P. R. Fina, M. Scalera, and G. Dimauro, "Personal heart health monitoring based on 1D convolutional neural network," J. Imag., vol. 7, no. 2, 2021, Art. no. 26. [Online]. Available: https://doi.org/10.3390/jimaging7020026

[23] Q. Zhang, D. Zhou, and X. Zeng, "HeartID: A multiresolution convolutional neural network for ECG-based biometric human identification in smart health applications," IEEE Access, vol. 5, pp. 11805–11816, 2017. [Online]. Available: https://doi.org/10.1109/ACCESS.2017.2707460

[24] U. R. Acharya, S. L. Oh, Y. Hagiwara, J. H. Tan, M. Adam, and R. S. Tan, "A deep convolutional neural network model to classify heartbeats,"Comput. Biol. Med., vol. 89, pp. 389–396, 2017.[Online]. Available: https: //doi.org/10.1016/j.compbiomed.2017.08.022

[25] R. Bharti, A. Khamparia, M. Shabaz, G. Dhiman, S. Pande, and P. Singh, "Prediction of heart disease using a combination of machine learning and deep learning," Comput. Intell. Neurosci., vol. 2021, 2021, Art. no. 8387680. [Online]. Available: https://doi.org/10.1155/2021/ 8387680

[26] S. Kiranyaz, T. Ince, and M. Gabbouj, "Real-time patient-specific ECG classification by 1-D convolutional neural networks," IEEE Trans. Biomed.Eng., vol. 63, no. 3, pp. 664–675, Mar. 2016. [Online]. Available: https://doi.org/10.1109/TBME.2015.2468589

[27] A. H. Khan, M. Hussain, and M. K. Malik, "Cardiac disorder classification by electrocardiogram sensing using deep neural network," Complexity, vol. 2021, 2021, Art. no. 5512243. [Online]. Available: https://doi.org/10. 1155/2021/5512243

[28] T. Rahman et al., "COV-ECGNET: COVID-19 detection using ECG trace images with deep convolutional neural network," 2021, arXiv:2106.00436.

[29] U. R. Acharya, H. Fujita, S. L. Oh, Y. Hagiwara, J. H. Tan, and M. Adam, "Application of deep convolutional neural network for automated detection of myocardial infarction using ECG signals," Inf. Sci., vol. 415– 416, pp. 190–198, 2017. [Online]. Available: https://doi.org/10.1016/j.ins. 2017.06.027