https://doi.org/ 10.33472/AFJBS.6.Si2.2024.584-593

African Journal of Biological Sciences

Journal homepage: http://www.afjbs.com

Research Paper Open Access

PREDICTING HEART ATTACK FROM RETINAL FUNDUS IMAGE CLASSIFICATION USING CNN WITH EFFICIENT NET B0

R.INDUMATHI
Assistant Professor
Department of CSE
Manakula Vinayagar
Institute of Technology,Puducherry
indu5490@gmail.com

Dr. N.PALANIVEL
Associate Professor
Department of CSE
Manakula Vinayagar
Institute of Technology,Puducherry
npalani76@gmail.com

AKASH.G
UG Scholar
Department of CSE
Manakula Vinayagar
Institute of Technology,Puducherry

AKASH.M
UG Scholar
Department of CSE
Manakula Vinayagar
Institute of Technology,Puducherry

FAYAZ.F
UG Scholar
Department of CSE
Manakula Vinayagar
Institute of Technology,Puducherry

Article History

Volume 6,Issue Si2, 2024

Received:10 Mar 2024

Accepted : 08 Apr 2024

doi: 10.33472/AFJBS.6.Si2.2024.584-593

Abstract- *This paper focuses on using advanced deep learning techniques to analyze fundus iris images for early detection of conditions like glaucoma, diabetes, and heart attacks. By exploiting the unique characteristics of retinal vasculature, the goal is to identify abnormalities that may indicate underlying cardiovascular risk. Our proposed sophisticated deep learning models such as CNNs with Efficient BO, the aim is to improve the accuracy and efficiency of early heart attack detection through noninvasive imaging. It utilizes a comprehensive dataset of fundus iris images, crucial for advancing cardiovascular disease applications. These images are processed to extract relevant features indicative of heart disease presence. Developing and training deep learning models is a key part of this process, focusing on identifying vascular anomalies suggestive of cardiovascular risk. The system's effectiveness is evaluated rigorously using metrics like sensitivity and positive predictive value (PPV) to ensure accurate discrimination between healthy and unhealthy conditions with high confidence. This paper represents a significant advancement in ophthalmology, offering a promising avenue for early heart attack detection and prevention of associated complications*

Keywords: Convolutional network (CNN), B0 is Intercep, Cardivasicular, Heart attack, Fundus iris images

I.INTRODUCTION

Digital computer processing involves creating and manipulating a two-dimensional image, also known as a digital picture, which is a finite array of real or complex numbers represented by a finite amount of bits. An image that is provided as an X-ray, slide, transparency, picture, or other format is first digitally converted and saved in computer memory as a binary digit matrix. After being digitalized, this picture can be processed and/or shown on a TV monitor with high definition. This study focuses on the use of retinal fundus images for heart attack risk prediction, using machine learning algorithms to analyze intricate patterns and abnormalities within these images. The retina serves as a vital indicator of systemic health conditions, including cardiovascular health. The proposed methodology uses state-of-the-art image classification algorithms to accurately identify and categorize specific features in retinal fundus images, such as vascular changes and microaneurysms, indicative of underlying cardiovascular issues. The machine learning model learns to correlate these patterns with the likelihood of an individual experiencing a heart attack. The field of medical imaging and machine learning and holds the potential to revolutionize cardiovascular risk assessment by integrating non-invasive retinal imaging with advanced computational models. This proactive approach could significantly impact public health by enabling timely interventions.

1. IMAGE PROCESSING FUNDAMENTAL

Image processing is a subcategory of digital signal processing that uses computer algorithms to convert images into digital form. It offers advantages over analog image processing, such as a wider range of algorithms and avoiding noise and signal distortion issues. Digital image processing can be modelled as multidimensional systems. Image processing is a rapidly growing technology utilizing two-dimensional signals and established methods, with applications in various business sectors and a core research area in engineering and computer science. Images are captured by video cameras and processed through five fundamental processes, allowing for more complex algorithms and sophisticated performance. recognition, projection, and multi-scale signal analysis.

2. IMAGE ENHANCEMENT:

Image enhancement operations, like contrast, brightness, noise reduction, and detail sharpening, improve image quality by enhancing the clarity of the same information without adding new information.

3. IMAGE RESTORATION:

Image restoration corrects degradations in original images, addressing issues like improper focus, and camera motion, aiming improve overall image quality.

4. IMAGE COMPRESSION:

Image compression is techniques used to reduce data content, remove redundant information, and reduce size for efficient storage or transportation. Lossless compression preserves the original image's data but offers excellent compression.

5. IMAGE SYNTHESIS:

Image synthesis is take images from non-image file, often creating images that are physically or impractically impossible to acquire.

II. LITERATURE SURVEY

Sharon Rose. J et.al (2023) This paper focus the machine learning models to predict heart attacks using a Kaggle dataset. The model employs k-modes clustering, random forest, decision tree classifier, multilayer perceptron, and XGBoost, with GridSearchCV optimizing parameters. The study demonstrates that using various parameters and classifiers, a feasible prognosis method can be achieved, with Logistic Regression achieving the highest accuracy and precision [1]. Rizwan Ahmed Khan (2023) it presents an AI-based model for clinicians and cardiologists to predict heart attacks using a 303-item dataset. The K-Nearest Neighbor algorithm was found to be the best, with an accuracy of 90.16% and recall of 87.09%. This model can predict specific cardiac disorders, such as right-heart disease using Jugular Venous Waveform, improving healthcare and reducing cardiovascular disease mortality rate [5]. Paras Negi and Manoj Kumar Bisht (2022) This paper uses machine learning to predict heart attack risk using data like age, gender, and A predictive model was developed using various datasets and tested for accuracy, revealing that heart disease is influenced by factors like cholesterol, genetic heart disease, high blood pressure, low physical activity, obesity, and smoking. Heart attacks are primarily caused by blood stoppage in coronary arteries. The findings can help develop more accurate methods and reduce heart attack-related deaths[7]. Niharika Thakur and Mamta Juneja (2022) Retinal fundus images have become increasingly used for diagnosing retinal diseases like glaucoma, which damage the optic nerve and affects vision. This paper investigates various segmentation methods for glaucoma diagnosis, aiming to enhance accuracy in identifying and classifying Despite the ongoing challenge of ganglion cell exit, the optic disc and optic cup have been successfully maintained[8]. Kaushik Mitra and Sivaprakasam (2021) A new architecture using fully convolutional networks (FCNs) is proposed for the study focuses on glaucoma screening, enhancing the cup-to-disc ratio (CDR), and minimizing vision loss. The architecture uses residual learning and adversarial training for segmentation, without complex preprocessing techniques. Experiments on 159 images from the RIM-ONE database show the proposed method outperforms existing methods in various evaluation metrics for disc and cup segmentation [13]. Julian Zilly Joachim and M. Buhmann (2020) The authors provide an innovative method to retinal image segmentation with convolutional neural network architectures based on ensemble learning. They offer a learning framework for convolutional filters, apply an entropy sampling technique, then put them through an unsupervised graph cut algorithm and convex hull transformation[14].

III. PROPOSED WORK

Our proposed system aims to detect heart attacks using innovative deep learning models, specifically leveraging Convolutional Neural Networks (CNN) with efficient backpropagation optimization. The heart attack detection technique employed by these deep learning models focuses on maximizing both F1 score and accuracy metrics.

A. SYSTEM ARCHITECTURE

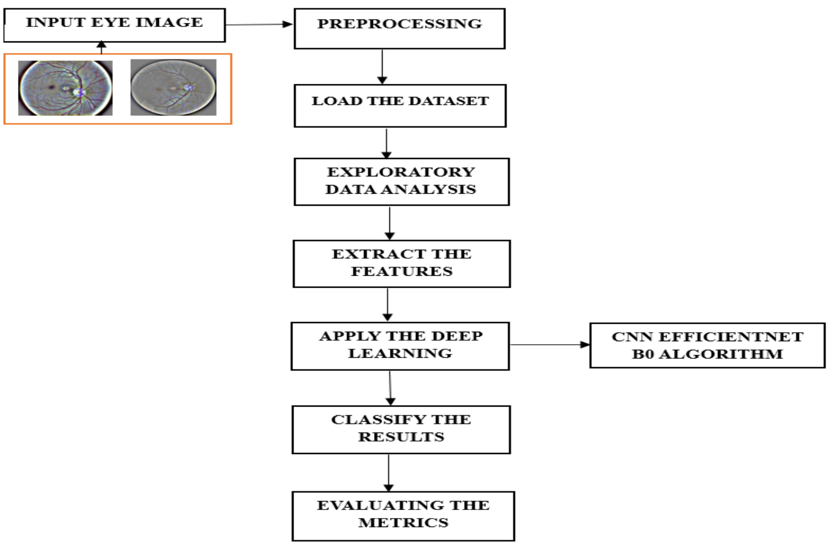

Fig 1: System Architecture

B. MODULES

- Data Collection and Preprocessing: The first step involves collecting fundus iris images from patients, including those with and without heart attacks. These images are then preprocessed to enhance their quality and ensure that they are suitable for analysis. This may involve resizing images, adjusting contrast, and removing noise.
- Feature Extraction: Deep learning models are utilized to identify heart attack patterns in fundus iris images by adjusting the model's weights based on the training data, after feeding the images.

- Model Training and Validation: The trained model is then used to predict heart attacks in new, unseen fundus iris images. The model's predictions are validated using a separate set of images to assess its accuracy and reliability.
- After validation and refinement, can be deployed to analyze fundus iris images in real-time or in batches. The model's performance is continuously monitored to ensure that it remains accurate over time.

C. DATA COLLECTION

The study focuses on predicting heart attack risk using retinal fundus images, a dataset that includes a diverse range of images from various sources such as medical databases, clinics, and research institutions. The dataset includes images of blood vessels, optic disc, and surrounding structures from individuals with varying cardiovascular risk profiles, including those with a history of heart attacks. The inclusion of images from diverse age groups, genders, and ethnic backgrounds minimizes biases and improves the model's applicability to a broader population. Ethical considerations and patient privacy are prioritized during the data collection process, with all data anonymized and protected by privacy regulations. The study adheres to established ethical guidelines and institutional review board approvals for transparent research practices.

Fig 2: Dataset of eye retinal

The process of collecting data for heart attack risk prediction using eye retinal fundus images is a complex one. It involves acquiring diverse retinal images from individuals from various demographics, including age, gender, and ethnic backgrounds, to ensure the model's generalizability across different populations and enhance its applicability in real-world scenarios. Collaboration with healthcare institutions and expert ophthalmologists is crucial for establishing ground truth labels, which include relevant features like vascular changes and microaneurysms. The quality and resolution of the retinal images are also crucial for the effectiveness of the machine learning model.Privacy and ethical considerations are paramount during data collection, with strict adherence to data protection regulations and techniques may be employed to safeguard individual identities while preserving the dataset's integrity. Longitudinal data is essential for tracking changes in retinal features over time, allowing for a dynamic understanding of cardiovascular risk progression. Regular follow-ups and periodic image updates contribute to the temporal dimension of the dataset, enhancing the model's predictive capabilities. Data augmentation techniques like rotation, scaling, and flipping artificially diversify datasets, preventing overfitting and enhancing model generalization to unseen data.

Continuous feedback loops between machine learning researchers and healthcare professionals further refine the dataset and address emerging challenges. Regular updates to the dataset reflect advancements in medical knowledge and technology, and collaboration with the scientific community for dataset sharing and benchmarking foster transparency and accelerate progress in the field.

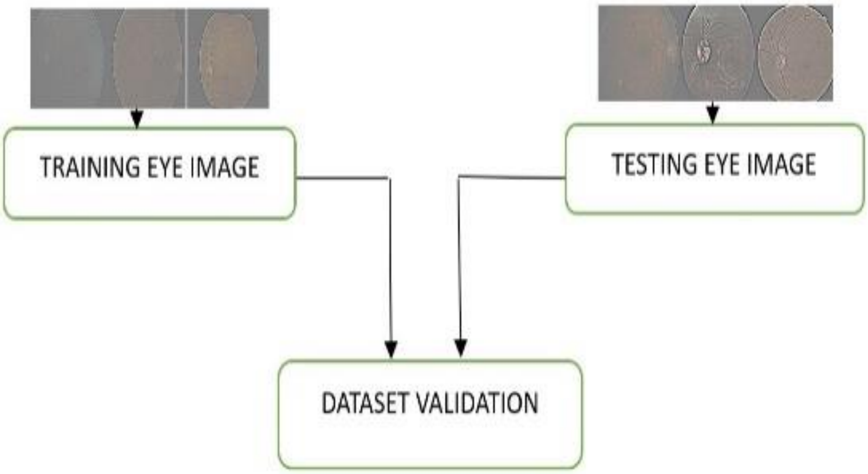

Fig 3: Data validation process

D. MODEL PARAMETERS

The heart attack risk prediction model uses retinal fundus images for image classification, utilizing Convolutional Neural Networks (CNNs) [13] with a focus on the EfficientNet B0 architecture. The model's efficiency and scalability make it a suitable choice for predicting cardiovascular risk. EfficientNet B0's depth-wise separable convolutions and compound scaling enable effective feature extraction from retinal fundus images, capturing intricate details essential for cardiovascular risk assessment[9]. The training phase involves fine-tuning model parameters to improve the network's capacity to identify subtle heart attack risk patterns. Hyperparameters such as learning batch size, and regularization techniques are adjusted, and transfer learning is employed to leverage knowledge from diverse visual features. Input data preprocessing is tailored to the characteristics of retinal fundus images, using techniques like normalization, augmentation, and cropping to generalize well across various fundus image variations while minimizing overfitting. Validation and fine-tuning of model parameters are performed iteratively to achieve a balance between sensitivity and specificity in heart attack risk prediction.

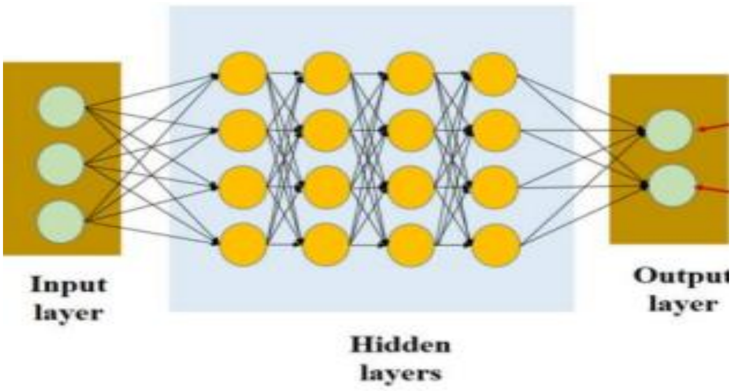

Fig 4: CNN Model

IV. PERFORMANCE METRICS

The study evaluates the effectiveness of a model for heart attack risk prediction using eye retinal fundus images and Convolutional Neural Network (CNN), specifically EfficientNet B0. Key metrics evaluate a model's accuracy, robustness, and reliability, with accuracy indicating the overall correctness of its predictions. but it may not be sufficient in medical applications where imbalances between classes are prevalent. Precision and recall provide a more nuanced understanding of the model's performance, highlighting the model's ability to make accurate positive predictions and identifying all actual positive instances. Balancing precision and recall is crucial in the medical domain to ensure sensitivity and specificity. The F1 score is a measure of precision and recall offers a harmonized measure of a model's performance, particularly useful when striving for a balanced trade-off To distinguish between positive and negative values across different thresholds, a ROC curve can be used to measure a model's ability.In conclusion, the performance metrics of heart attack risk prediction using retinal fundus images and EfficientNet B0 provide a comprehensive assessment of the model's predictive capabilities, aiding in determining its clinical viability and potential for real-world application in cardiovascular risk assessment.

The confusion matrix can be determined by identifying the following parameters:

- **Accuracy:** The percentage of the total number of correct predictions.

$$\textbf{Accuracy} = \frac{\textbf{True}_{\textbf{positive}}+\textbf{True}_{\textbf{negative}}}{\textbf{True}_{\textbf{positive}}+\textbf{True}_{\textbf{negative}}+\textbf{False}_{\textbf{positive}+\textbf{False}_{\textbf{negative}}}}$$

- **Positive Predictive Value or Precision:** Identified the correct percentage of positive cases.

$$\textbf{Precision} = \frac{\textbf{True}_{\textbf{positive}}}{\textbf{True}_{\textbf{positive}+\textbf{False}_{\textbf{positive}}}}$$

- **Negative Predictive Value** Identified the correct percentage of negative cases.
- **Sensitivity or Recall:** Identified the correct percentage of positive cases.

$$\textbf{Recall}=\frac{\textbf{True}_{\textbf{positive}}}{\textbf{True}_{\textbf{positive}+\textbf{False}_{\textbf{negative}}}}$$

The confusion matrix, a key component in binary and multiclass classification problems, can be calculated using the Scikit-learn metrics module in Python. The four metrics, accuracy, precision, discussed, with each defined based on various examples.

MODELS	ACCURACY
CNN WITH EFFICIENTNET B0	96.12
ADABOOST	92.08
K-Nearest Neighbor algorithm	90.01
RNN	82.20

Table1: **Result analysis of deep learning Models**

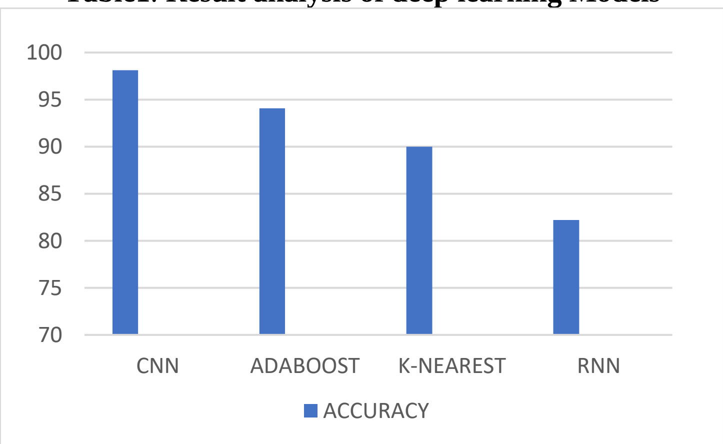

Figure 5: Result analysis of deep learning Models

V. EXPREIMENTAL RESULT

The research focuses on the use of EfficientNetB0 for predicting heart disease stages from retinal eye images. The process involves several steps such as data collection, pre-processing, model selection and training, evaluation and validation, deployment and monitoring, and retraining.

Data collection involves resizing retinal eye images to the expected input size, normalizing pixel values, and possibly augmenting the dataset undergoes transformations, and a model is selected and trained using an optimizer and loss function. Evaluation and validation involve splitting the dataset into training, validation, and test sets. The model is trained on the training set, monitored on the validation set, and adjusted as needed for improved accuracy.

The model's performance on the test set is continuously monitored and retrained with new data to maintain its accuracy. If training with EfficientNetB0 results in high validation loss and low accuracy, several factors and potential solutions should be considered. These include input data normalization, model compilation with the correct loss function and optimizer, data augmentation using Image Data Generator,

Input data normalization ensures that the model's built-in normalization is applied consistently across training and validation data, while model compilation ensures that the model is compiled with the correct loss function and optimizer.

Overfitting vs. underfitting can indicate that the model is learning. Regularization techniques like dropout or weight decay can help mitigate overfitting in training data, while adjusting the model architecture, such as reducing complexity or adding regularization layers, may improve validation performance.

OUTPUT AND ACCURACY:

We have given to our model with set of input images will be fed into the layer **[8]** and we get the output as images labelled with the stages of heart attack it belongs to such as Mild, Moderate, Normal, Proliferate and Severe.

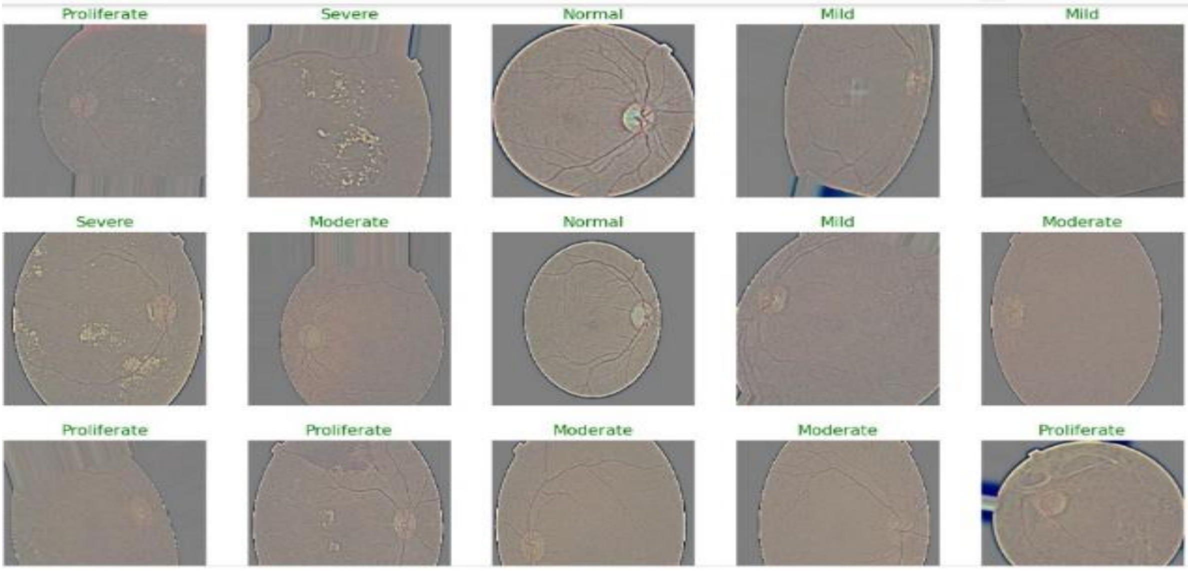

Fig 6: Output of the model

ACCURACY:

We train our model through several batches by dividing the number of training sets into groups called Epoch. The accuracy at which our model predicts to each epoch is shown by using the fellowing graph. The accuracy we got for 5 epoch is 95.149.

Starting training using base model EfficientNetB1 training all layers

Epoch	Loss	Accuracy	V_loss	V_acc	LR	Next LR	Monitor	Duration
1 /5	1.214	84.784	1.30048	75.931	0.00100	0.00100	accuracy	70.50
2 /5	0.887	89.369	1.04233	79.654	0.00100	0.00100	accuracy	69.45
3 /5	0.691	91.628	0.92555	80.585	0.00100	0.00100	val_loss	69.64
4 /5	0.551	93.189	0.89256	78.457	0.00100	0.00100	val_loss	69.23
5 /5	0.437	95.149	0.84056	78.989	0.00100	0.00100	val_loss	69.59

Training is completed - model is set with weights for the epoch with the lowest loss

Fig 7: Accuracy Calculation

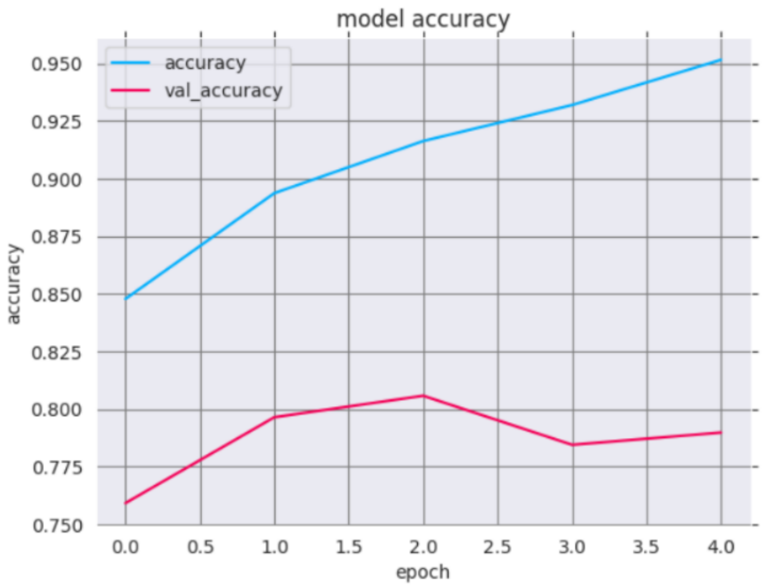

Fig 8: Accuracy Graph

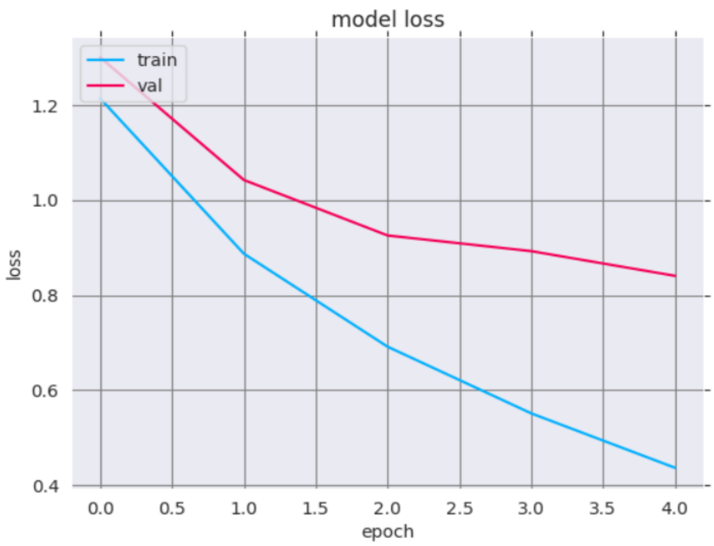

Fig 9: Model Loss Graph

PERFORMANCE METRICS:

The performance metrics are calculated by using the above formulas and the percentage of precision, recall and fi-score for accuracy, macro average and weighted average for our model is given below and there is a classification report and graph.

	PRECISION	RECALL	F1-SCORE
0	0.80	1.00	1.00
1	0.88	0.88	0.88
2	1.00	0.93	0.93
3	1.00	1.00	1.00
4	1.00	1.00	1.00
ACCURACY			0.95
MACRO_AVG	0.93	0.96	0.95
WEIGHTED_AVG	0.96	0.95	0.95

Table 2: Classification Report Table

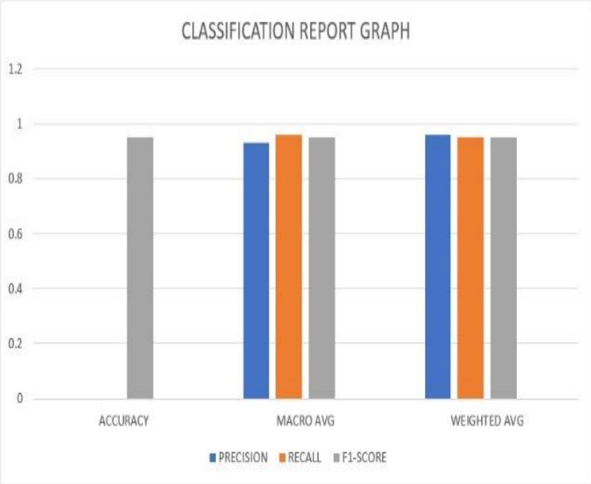

Fig 10: Performance graph

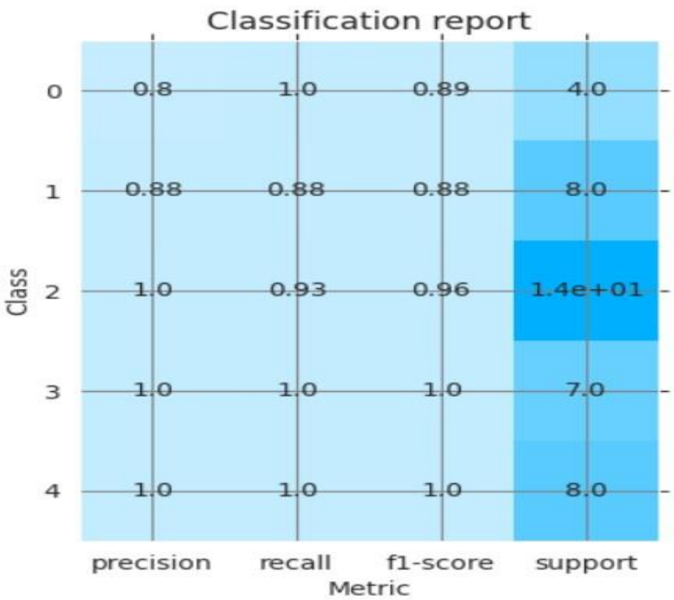

Fig 11: Classification Report

The above figure shows the classification metrics for each class and it shows the percentage of precision, recall and F1-score.

VI. CONCLUSION

The pandemic has led to a rise in heart attacks, diabetes, and obesity among young people, with work schedules contributing to increased sickness rates. To combat this issue, early detection is crucial. A model has been developed to predict the risk of obesity, diabetes retinal fundus images, and heart attacks based on user input. Health risk assessment is crucial for identifying urgent health conditions and taking necessary precautions. The proposed system aims to create a user-friendly AI-driven health risk assessment application that allows users to perform basic assessments. CNN with Efficient Net B0 algorithm-based health predictors generate health analysis reports and provide guidance. The model predicts the risk of obesity, diabetes retinal fundus images, and heart attacks based on user input. The evaluation of a person's health risk is crucial for identifying illnesses that require immediate attention, enabling individuals to identify potential health risks and implement necessary safety measures. The system aims to create an easy-to-use application that uses AI to drive health risk assessment, providing users with a platform for basic assessments.

REFERENCES

[1] Sharon Rose. J Mar 17, 2023"Heart Attack Prediction Using Machine Learning Techniques"

[2] N. Palanivel, "Novel Implementation of Heart Disease Classification Model using RNN Classification" in IEEE - International Conference on System, Computation, Automation and Networking (ICSCAN2023), 2023.

[3] N Palanivel, V Keerthana, N Monisha, S Sandhiya (2023) "Object Detection and Recognition In Dark Using YOLO" Journal of Data Acquisition and Processing 38 (2), 57 2023

[4] N Palanivel "Design & Implementation of Real Time Object Detection using CNN" in IEEE - International Conference on System, Computation, Automation and Networking (ICSCAN2023)

[5] Rizwan Ahmed Khan"A Non-Newtonian Model of Two Phase Hepatic Blood Flow in Capillary during Jaundice Newtonian Model of Two Phase Hepatic Blood Flow in Capillary during Jaundice" November 2022

[6] R. Indumathi, N Palanivel, V Kumar, JM Ahmed, (2022) "Alzheimer's Disease Detection using Deep Neural Network" Telematique, 4210-4217 (2022)

[7] Paras Negi and Manoj Kumar Bisht, "Analysis and Prediction of Heart Attack using Machine Learning Models" November 2022 10.1109/ICCCS55 188.2022.10079409

[8]Mamta Juneja, Sarthak Thakur, Archit Uniyal, Anuj Wani, Niharika Thakur, Prashant Jinda'Deep learning-based classification network for glaucoma in retinal images" July 2022, 108009

[9] F. Shi et al., "Review of Artificial Intelligence Techniques in Imaging Data Acquisition, Segmentation, and Diagnosis for COVID-19," IEEE Rev. Biomed. Eng., vol. 14, pp. 4–15, 2021, doi: 10.1109/RBME.2020.2987975.

[10] N. Siddique, S. Paheding, C. P. Elkin, and V. Devabhaktuni, "U-Net and Its Variants for Medical Image Segmentation: A Review of Theory and Applications," IEEE Access, vol. 9, pp. 82031–82057, 2021, doi: 10.1109/ACCESS.2021.3086020.

[11] S. Soffer et al., "Deep learning for pulmonary embolism detection on computed tomography pulmonary angiogram: a systematic review and meta-analysis," Sci Rep, vol. 11, no. 1, p. 15814, Aug. 2021, doi: 10.1038/s41598-021-95249-3.

[12] N. Chaosuwannakit, W. Soontrapa, P. Makarawate, and K. Sawanyawisuth, "Importance of computed tomography pulmonary angiography for predict 30-day mortality in acute pulmonary embolism patients," European Journal of Radiology Open, vol. 8, p. 100340, 2021, doi: 10.1016/j.ejro.2021.100340.

[13] Sharath M S Hankaranarayana, Keerthi Ram, Kaushik Mitra, Mohanasankar Sivaprakasam, "Monocular Retinal Depth Estimation and Joint Optic Disc and Cup Segmentation using Adversarial Networks", 2020

[14**]** Julian Georg Zilly, Joachim M Buhmann, Dwarikanath Mahapatra, **"**Boosting Convolutional Filters with Entropy Sampling for Optic Cup and Disc Image Segmentation from Fundus Images" October 2020