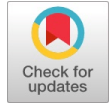


A Framework for the Prediction of Eye Diseases using Deep Learning Models



Madhab Paul Choudhury, Jagannibas Paul Choudhury

Abstract: Artificial Intelligence (AI) has significantly enhanced various aspects of our lives, providing practical solutions to complex problems and narrowing the gap between real-world challenges and business needs. Within the realm of AI, innovative technologies such as machine learning and deep learning have revolutionised the way we analyse data, make informed decisions, and respond to complex situations, all with the goal of understanding and resolving them efficiently. As data generation and storage continue to expand rapidly, these technologies have become essential in managing data analytics, storage systems, and decision-making frameworks. Through digital transformation, industries are being reshaped, and global services—especially in fields such as healthcare—are being enhanced to improve the quality of human life. The eye is considered the most important sensory organ for humans, playing a vital role in their overall ability to interact with the world. Unfortunately, many individuals in both rural and urban areas suffer from eye conditions such as cataracts, glaucoma, ocular hypertension, bulgy vision, etc., that affect their vision. There are various causes, including age, diabetes, and genetic and hereditary factors. Modern lifestyles, which have led to increased use of displays for digital devices, are also a factor affecting vision. This study aims to develop a predictive model for vision-related diseases by leveraging medical data and analyzing the influence of various contributing factors using deep learning methodologies. Early detection of eye conditions is crucial to prevent serious complications, as timely diagnosis plays a vital role in ensuring effective treatment. Conducting thorough assessments to identify potential indicators of eye diseases is highly encouraged. Deep learning and artificial intelligence (AI) significantly enhance the ability to detect these illnesses at an early stage. The purpose of this research is to lay the foundation for discovering a robust and adaptable solution. Specifically, the study focuses on reviewing the classification of eye diseases using advanced deep learning models, such as Custom CNN (Convolutional Neural Network), VGG16, ResNet, InceptionV3, GoogleNet, EfficientNet B2, MobileNet, and DenseNet 121. The proposed classification framework follows a series of steps: initially, it involves gathering widely accessible datasets related to eye diseases and performing data preprocessing to ensure consistent experimental conditions. The primary objective is to train the model to accurately identify symptoms of eye diseases, rather than optimizing for a narrow subset of data. Given the success of deep learning in image classification and object recognition tasks, the research emphasizes these modern techniques over conventional handcrafted approaches.

Keywords: Custom CNN (Convolution Neural Network), VGG16, ResNet, InceptionV3, GoogleNet, Efficient Net B2, MobileNet, DenseNet 121.

Abbreviations:

CVD: Cardiovascular Disease
DN: Diabetic Nephropathy
RF: Random Forest
PSO-GWO: Particle Swarm Optimization-Grey Wolf Optimization
GANs: Generative Adversarial Networks
PSS: Posterior Scleral Staphylomas
VH: Vitreous Haemorrhages
FCNN: Fully Convolutional Neural Network
CKD: Chronic Kidney Disease
DSCNN: Deep Separable Convolutional Neural Networks
CLAHE: Contrast Limited Adaptive Histogram Equalisation
ENN: Edited Nearest Neighbours
IHT: Instance Hardness Threshold
SMOT: Synthetic Minority Oversampling Technique
DSC: Dice Similarity Coefficient
MIAS: Mammographic Image Analysis Society
LSTM: Long Short-Term Memory
DDSM: Digital Database for Screening Mammography
PaLM: Pathology Learning and Modelling
SVM: Support Vector Machine
KNN: K Nearest Neighbours
ML: Machine Learning
CNN: Convolutional Neural Network
KPCA: Kernel Principal Component Analysis
GEO: Gene Expression Omnibus
IOLC: Identification of Lung Cancer
AI: Artificial Intelligence

I. INTRODUCTION

Eyes are an essential part of human life; every person relies on their eyes to see and sense the world around them. One of the most vital senses is sight, as it accounts for approximately 80% of all available information. By taking proper care of your eyes, the risk of developing blindness and losing vision decreases, while also being vigilant for any emerging eye conditions, such as glaucoma and cataracts. Most people experience eye issues at some point in time. Some eye issues are minor and can be easily treated at home, often resolving on their own. Other major eye issues require assistance from expert doctors. Many eye conditions, including trachoma, cataracts, and corneal ulcers, can impair vision. Only when these eye illnesses are effectively diagnosed at an early stage can the progression of the disease be halted. These eye illnesses have a wide range of visually discernible symptoms. Early detection of eye disease is essential for effective treatment.

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*Correspondence Author(s)

Madhab Paul Choudhury, Research Scholar, Department of Computer Science & Engineering, IIT ISM Dhanbad, Jharkhand, Kolkata (West Bengal), India. Email ID: babunmadhab@gmail.com

Dr. Jagannibas Paul Choudhury*, Retired Professor (IT), Kalyani Government Engineering College, Kalyani, West Bengal, Professor, Department of Computer Science & Engineering, Narula Institute of Technology, Kolkata (West Bengal), India. Email ID: jnpckgec@gmail.com, ORCID ID: [0000-0002-0575-6670](https://orcid.org/0000-0002-0575-6670)

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II. LITERATURE REVIEW

The research paper [1] focuses on utilizing emerging technologies to predict the progression of Periodontitis, a prevalent oral disease. Machine learning classifiers are used to analyse and forecast the development of the disease. The study also incorporates techniques like cross-validation, feature extraction, and ensemble learning, which are evaluated for their effectiveness. The performance of various classifiers, including Naïve Bayes, Support Vector Machine (SVM), Random Forest, Logistic Regression, K Nearest Neighbours (KNN), and Decision Tree, is compared. These classifiers are tested on a dataset of 1000 periodontitis patients, yielding remarkable accuracy rates: 95.5%, 100%, 100%, 100%, 99.5%, and 99% for the classification of chronic localised and chronic generalised periodontitis, respectively.

Early detection and understanding the underlying causes of diabetes can significantly enhance patient outcomes and public health initiatives [2]. To achieve this, a comprehensive dataset comprising medical records from individuals both with and without diabetes is collected, encompassing various demographic, lifestyle, and clinical factors. Feature engineering techniques are applied to preprocess the data and identify relevant features. Accurate prediction models for assessing diabetes risk are developed using diverse machine learning algorithms, including Decision Trees, Random Forests, and Support Vector Machines. Additionally, by examining disease influence measures, the primary contributors to diabetes development are identified.

The authors [3] propose a framework for multi-class skin disease classification that combines a robust convolutional neural network (CNN), MobileNet V2 (MNv2), and Long Short-Term Memory (LSTM) to enhance the accuracy and reliability of diagnoses. This approach leverages LSTM's ability to manage multi-class classification tasks and CNN's strength in automatically learning distinguishing features from raw skin images. The proposed method surpasses previous models, achieving an accuracy of over 87%, using the HAM10000 dataset for evaluation.

Automated systems in healthcare now generate clinical records, predict infections, assist in diagnostics, and enable continuous patient monitoring [4]. The integration of Internet of Things (IoT) devices and Machine Learning (ML) algorithms has been pivotal in this transformation. However, the performance of AI algorithms can vary across different datasets, leading to inconsistencies in predictive outcomes. Such variability poses potential risks to clinical decision-making processes. This paper presents key features of prominent ML algorithms used for classification and prediction, illustrating their applications in the healthcare sector.

Machine learning models can analyse gene expression data from DNA microarrays to predict the presence of lung cancer in patients [5]. Collective Random Forest and Adaptive Boosting are utilized to identify the contributing factors. Kernel Principal Component Analysis (KPCA) is employed for feature reduction, followed by calculating the correlation between each feature and the target using KPCA's statistical parameters. One method of assessing a classification model's accuracy is by determining the proportion of correct

predictions for a given dataset. In this study, the proposed technique is validated using a dataset containing lung cancer-related information, specifically GSE4115 from the Gene Expression Omnibus (GEO) database, along with its expression profiles. The results highlight the effectiveness of the Identification of Lung Cancer (IOLC) model, which achieves an accuracy of 81%, a precision of 81.2%, a recall of 78.9%, an F-Measure of 77.7%, and an error rate of 0.29%.

The advancement of intelligent and sustainable healthcare services is significantly propelled by the integration of Internet of Things (IoT) devices and cloud-based infrastructure [6]. By adopting a cloud-centric IoT paradigm, machine learning methods can enhance the capabilities of innovative healthcare systems. In this approach, data collected from IoT devices is securely transmitted to the cloud for further analysis and processing. Machine learning algorithms then analyse this data to extract valuable insights, facilitating more informed healthcare services. Continuous training and updating of these models with the vast amounts of data stored in the cloud enable progressive improvements in their accuracy and performance. This framework aims to achieve intelligent and sustainable healthcare solutions by effectively combining machine learning techniques with cloud-centric IoT.

Machine learning has become a vital tool in the medical field, utilising data patterns to improve diagnostic accuracy. This paper [7] aims to minimize misdiagnosis and improve patient outcomes by developing a predictive model for cardiovascular diseases using machine learning techniques. The study focuses on accurately classifying cardiovascular conditions, enabling healthcare professionals to make informed decisions for timely and targeted treatments. The findings highlight the significant role of machine learning in medicine, demonstrating its potential to lower mortality rates associated with cardiovascular diseases. By applying ensemble classification methods to a dataset of patients with heart disease, the research aims to improve prediction accuracy.

This study examines the application of Pathology Learning and Modelling (PaLM) methodologies to enhance biomedical machine learning research for interpreting medical data [8]. PaLM involves developing and applying machine learning algorithms to analyze pathology data, including histological images, molecular pathology information, and clinical pathology details. By harnessing machine learning capabilities, PaLM enables researchers to uncover hidden patterns, correlations, and insights within complex medical datasets. The authors aim to enhance disease diagnosis, prognosis, and treatment planning by precisely and efficiently analysing pathology data using machine learning models and algorithms. Integrating molecular pathology data, clinical data, and pathology images provides a comprehensive understanding of diseases, supporting personalised patient management. PaLM approaches facilitate automated image analysis and segmentation, extraction of relevant features, and identification of disease-specific patterns.

This study presents an advanced approach for kidney stone prediction using a deep learning framework that integrates



the YOLO v7 model with the Energy Valley optimizer for image segmentation and the Pulse Couple Neural Network (PCNN) for classification [9]. Initially, the YOLO v7 model is used to detect and localise kidney stones for segmentation purposes. To enhance its performance, hyperparameter tuning is conducted, enabling the model to learn and generalise from the data effectively. The Energy Valley optimiser, inspired by energy valleys in physics, is introduced to further optimise YOLOv7, thereby improving its segmentation accuracy. Additionally, the PCNN model is utilized as a classification framework, leveraging pulse-coupled oscillators to analyse the segmented kidney stone regions and identify their characteristics. The proposed methodology demonstrates exceptional performance across multiple evaluation metrics, achieving a precision of 98.58%, a recall of 99.17%, an accuracy of 98.88%, an F1-score of 97.42%, and a specificity of 98.23%.

This study evaluates the performance of various machine learning and deep learning models, including convolutional neural networks (CNNs), decision trees, random forests, extra trees classifiers, dense models, and hybrid CNN-LSTM architectures, in classifying electrocardiogram (ECG) signals for disease detection [10]. An extensive review of existing literature on machine learning applications in ECG signal processing and healthcare is conducted. The research utilises a meticulously curated and annotated dataset comprising ECG signals from both healthy individuals and patients with significant disorders, ensuring a comprehensive representation of the target population. In binary classification tasks, CNN and CNN-LSTM models consistently outperform other algorithms, achieving high accuracy, F1-scores, and AUC-ROC values. These models effectively distinguish between disease and non-disease categories, demonstrating their potential clinical utility. The findings underscore the efficacy of CNN and CNN-LSTM models in enhancing diagnostic accuracy, thereby contributing to improved patient outcomes. The study also provides recommendations for future research and development in ECG signal processing, addressing challenges and considerations relevant to the implementation of these algorithms.

The authors have developed a risk assessment model that utilises convolutional neural networks (CNNs) to evaluate a patient's likelihood of hospitalisation or mortality due to heart failure within a large health maintenance organisation [11]. This study highlights the potential of deep learning algorithms for the early detection of heart disease. The primary goal of the research is to assess the accuracy of diagnosing cardiac conditions in individuals. Instead of determining the optimal partition order, the recursive partitioning process follows a greedy approach for reordering partitions. The proposed system utilises a CNN model to process input datasets for disease prediction, incorporating preprocessing, feature extraction, and classification techniques to analyse data and generate meaningful insights. By applying dimensionality reduction, the model enhances prediction accuracy using the same dataset. Notably, many conventional AI-based classification algorithms fail to surpass the accuracy levels achieved by Lasso or Ridge regression, both of which consistently deliver superior results.

The proposed approach by the authors integrates Long Short-Term Memory (LSTM) for sequence learning and Convolutional Neural Networks (CNNs) for extracting nonlinear features [12]. This methodology enhances the analysis of the Mammographic Image Analysis Society (MIAS) dataset, achieving improvements of 5% in accuracy, 6% in precision, and 4.6% in recall. The effectiveness of this approach is further validated using the INBREAST and Digital Database for Screening Mammography (DDSM) datasets through various performance metrics. Compared to existing methods, the proposed approach demonstrates a 2-3% increase in accuracy, a 2% improvement in precision, and a 3-4% boost in recall for the DDSM dataset. Similarly, in the INBREAST dataset, it enhances accuracy by 3-4%, precision by 2-3%, and recall by 4%, showcasing its effectiveness in mammographic image analysis.

Mammography has demonstrated promising outcomes with the application of deep learning technologies in the quantitative evaluation of parenchymal density, categorization, detection, diagnosis, and breast cancer risk prognosis, enabling more precise patient management. Additionally, deep learning has streamlined the interpretation process, reducing both the time required for interpretation and the associated workload. However, more comprehensive research is needed to definitively confirm the effectiveness of deep learning. This article examines the classification of mammograms using deep learning techniques and explores their potential for mammography interpretation, as well as the challenges they face in real-world applications. The proposed method combines Long Short-Term Memory (LSTM) for sequence learning and Convolution Neural Networks (CNN) for nonlinear feature mapping to enhance the accuracy of the Mammographic Image Analysis Society (MIAS) dataset by 5%, precision by 6%, and recall by 4.6%. Experiments using the INBREAST and Digital Database for Screening Mammography (DDSM) datasets validate the proposed approach, demonstrating improvements over existing methods. Specifically, it improves accuracy by 2-3%, precision by 2%, and recall by 3-4% on the DDSM dataset, and boosts accuracy by 3-4%, precision by 2-3%, and recall by 4% on the INBREAST dataset.

This paper presents a comparative analysis of segmentation and feature extraction methods for detecting lung cancer [14]. Various segmentation techniques, including thresholding, global Thresholding, and watershed segmentation, are implemented and assessed. Additionally, feature extraction is applied to improve the performance of these segmentation techniques. The proposed method is compared with existing approaches to showcase its effectiveness and potential for better lung tumour detection. The study uses five images for analysis, and the results indicate that the proposed segmentation and feature extraction techniques can achieve higher accuracy, potentially aiding in the early detection of lung cancer.

Segmentation, detection, and classification are essential stages in digital imaging pathology labs for analyzing MRI brain tumour regions. This study focuses on medical image analysis and classification using a convolution+ReLU algorithm, which integrates

convolutional techniques with ReLU optimization [15]. The research employs a robust and efficient convolution+ReLU approach on the BraTS 2020 dataset, significantly reducing segmentation time compared to other optimization methods. Furthermore, it demonstrates outstanding performance metrics, achieving 99.8% precision, 99% recall, and a 99.3% F-measure. Convolutional neural networks (CNNs) utilising the convolutional + ReLU activation function enhance learning speed and improve tumour analysis performance. In the experimental phase, the implemented convolution+ReLU model achieved an impressive accuracy of 99.8%, surpassing existing methodologies.

Researchers process extensive and complex healthcare data using various deep learning techniques, enabling medical professionals to predict diseases effectively [16]. This study presents a model designed to identify cardiac disorders, benefiting numerous individuals worldwide. The proposed model enhances the Convolution Neural Network (CNN), referred to as Custom CNN (C-CNN), and demonstrates superior performance compared to previously published methods.

The authors have focused on machine learning (ML) algorithms for cancer prediction, which are evaluated by various performance metrics [17]. By utilizing widely used ML techniques such as Support Vector Machines (SVM), K-Nearest Neighbours (KNN), Linear Regression, Decision Tree, and Naive Bayes, the study evaluates the accuracy of cancer prediction. Their research offers valuable insights and practical recommendations on applying machine learning techniques in clinical settings to improve cancer detection and patient care.

In this study, the authors propose enhancing a MobileNet base model by fine-tuning it with additional features to improve brain tumour detection [18]. The model's precision and accuracy are increased by restructuring its layers. Pre-processing techniques are applied to MRI images to enhance their quality, and data augmentation is employed to expand the dataset size, thereby improving the model's training process. The results indicate that the proposed model outperforms other convolutional neural network (CNN) models, including VGG16, Xception, and ResNet50, demonstrating the potential of deep learning in detecting brain tumours.

Since insulin plays a crucial role in regulating various properties of plasma, including water, enzymes, proteins, vitamins, and minerals, its imbalance can lead to diabetes [19]. Diabetes is one of the most prevalent chronic diseases worldwide. This research considers both clinical and non-clinical factors, including insulin levels, glucose levels, BMI, smoking status, stress levels, blood pressure, and dietary habits such as junk food consumption. The study aims to highlight the impact of these factors on an individual's likelihood of developing diabetes. Various machine learning techniques, including Support Vector Machines (SVM), Decision Trees, Random Forests, and Logistic Regression, are explored for predicting and analysing key features associated with diabetes. The authors conduct a comparative analysis of these techniques to assess their performance when incorporating both clinical and non-clinical parameters.

Existing methods [20] for medical image feature extraction have proven insufficient in addressing the challenges of

effectively detecting early brain tumours. To overcome this limitation, a novel model that leverages the Inception-v3 convolutional neural network has been proposed. This model enhances early identification of brain tumours by extracting and categorizing various features. Built upon the Inception-v3 architecture, it employs loss functions and the Adam Optimiser for hyperparameter optimisation, and utilises a softmax classifier for image classification into distinct categories. The model demonstrated a notable training accuracy of 99.02% and a validation accuracy of 89%, underscoring its potential in improving brain tumour detection.

The authors introduce an automated identification method that leverages deep learning and visual analysis technology [21]. Their approach classifies fundus images using a convolutional neural network (CNN) based on the severity of diabetic retinopathy (DR). This strategy involves image modification, designing an efficient CNN architecture, and utilizing a large dataset for model training. The results demonstrate the effectiveness of this technology in accurately detecting residual drug traces.

The article presents a fuzzy distance-based ensemble approach integrating deep learning models for cervical cancer detection in Pap smear images [22]. The methodology employs three transfer learning models—Inception V3, MobileNet V2, and Inception-ResNet V2—enhanced with additional layers to capture data-specific features. To combine the predictions from these models, the authors introduce a novel ensemble technique that minimizes the error between predicted and actual values. For cases with multiple predictions, three distance measures—Euclidean, Manhattan (also known as City-Block), and Cosine—are computed for each class relative to the optimal solution. These measures are then defuzzified using the product rule to determine the final classification. Experimental results show that Inception V3, MobileNet V2, and Inception ResNet V2 achieved accuracies of 95.30%, 93.92%, and 96.44%, respectively, individually. When the ensemble technique was applied, the overall performance improved to 96.96%, surpassing the individual models. The findings on three publicly available datasets confirm that the proposed model delivers competitive results compared to state-of-the-art approaches. This end-to-end classification method enhances cervical cancer detection in Pap smear images, enabling medical professionals to provide more effective treatment and improve the efficiency of the diagnostic process.

This study investigates the effectiveness of machine learning and deep learning models in detecting heart murmurs from audio recordings. Utilising the Physio Net Challenge 2016 dataset [22], the authors compare traditional machine learning models—Support Vector Machine, Random Forest, AdaBoost, and Decision Tree—with a Fully Convolutional Neural Network (FCNN). While ensemble methods, such as Random Forest and AdaBoost, improve robustness, they are still surpassed by deep learning techniques. The FCNN model, powered by artificial intelligence, outperforms all other models, achieving an accuracy of 0.99, a precision of 0.94, and a recall of 0.96. These findings underscore the potential of AI-driven

cardiovascular diagnostics, as deep learning models demonstrate superior ability in recognizing complex patterns in heart sound data. The study suggests that deep learning models provide significant advantages in medical diagnostics, particularly in cardiovascular health, by offering scalable and highly accurate solutions for heart murmur detection.

This paper presents a systematic literature review of pneumonia detection techniques that incorporate transfer learning alongside other methodologies [23]. The review protocol is meticulously designed to identify recent research on pneumonia detection from the past five years. Following an extensive search process, 35 studies were selected for analysis. The review summarizes these papers, comparing the effectiveness of various pneumonia detection methods based on their best-performing models. Additionally, the models are categorized into three primary approaches: deep learning methods, transfer learning techniques, and hybrid approaches. A comparative analysis of the top-performing models for pneumonia detection is also provided. The study concludes that while transfer learning demonstrates significant potential for enhancing pneumonia detection, further research is needed to refine these models for clinical use. Moreover, this review serves as a valuable resource for researchers by identifying existing research gaps in pneumonia detection techniques and suggesting directions for future advancements.

This study introduces a novel approach that utilises Deep Separable Convolutional Neural Networks (DS-CNNs) to enhance chronic kidney disease (CKD) prediction [24]. Using the Chronic Kidney Disease Dataset from Kaggle, the proposed model integrates DS-CNNs with advanced optimization techniques to improve predictive accuracy. DS-CNNs employ depth-wise and point-wise convolutions to enable efficient feature extraction and classification while maintaining computational efficiency. To further refine model performance, the Learning Rate Warm-Up with Cosine Annealing method is implemented, ensuring stable convergence and a controlled reduction in the learning rate. With an accuracy of 94.50%, the DS-CNN model surpasses traditional methods, offering superior predictive capabilities. These findings highlight the effectiveness of deep learning and optimization techniques in early CKD detection, presenting a promising tool for improved clinical decision-making.

The authors introduce and evaluate an innovative method for heart disease prediction by integrating deep learning models with bioinspired algorithms [25]. Deep learning techniques facilitate the automatic extraction of features and the recognition of complex patterns from raw data, while bioinspired algorithms enhance optimisation, thereby improving model accuracy and generalisation. Specifically, the cuckoo search algorithm and elephant herding optimisation algorithm are utilised to fine-tune the architecture and hyperparameters of deep learning models, thereby enabling an extensive exploration of different model configurations. This hybrid strategy effectively combines the strengths of deep learning and bioinspired optimisation, resulting in the development of highly effective predictive models. Experimental results on benchmark heart disease datasets confirm the superiority of the proposed approach

over traditional methods, demonstrating higher accuracy and robustness in predicting heart disease risk.

This study by the authors introduces an IoMT-enabled approach for detecting and classifying lung diseases, leveraging deep learning techniques to analyse lung sounds [26]. The proposed method utilizes three datasets: the Respiratory Sound, the Corona hack Respiratory Sound, and the Coswara Sound. To benchmark performance, traditional machine learning models such as the ExtraTree Classifier and AdaBoost Classifier are employed. The Extra Tree Classifier achieved accuracies of 94.12%, 95.23%, and 94.21% across the datasets, while the Ada Boost Classifier demonstrated improvements with accuracies of 95.42%, 96.33%, and 94.76%. In contrast, the proposed deep neural network (DNN) outperformed these models, achieving accuracies of 98.92%, 99.33%, and 99.36% across the same datasets, highlighting its effectiveness in lung disease classification.

Imbalanced classification poses a significant challenge in early disease detection and diagnosis using machine learning, often resulting in reduced accuracy due to the disproportionate distribution of positive cases compared to healthy individuals [27]. To enhance classification accuracy, this study proposes an architectural model that incorporates a modified Synthetic Minority Over-sampling Technique (SMOTE) with Minkowski distance and entropy-based weighting to determine the number of synthetic samples to generate. Additionally, feature selection is performed using a hybrid Particle Swarm Optimization-Grey Wolf Optimization (PSO-GWO) approach. The datasets used in the study are categorised based on feature count and total sample size into high-, medium-, and low-dimensional datasets. Six classification algorithms are evaluated across datasets for diabetes, heart disease, and breast cancer. The final results demonstrate average accuracies of 74% for diabetes, 83% for heart disease, and 96% for breast cancer. The proposed approach effectively addresses class imbalances in medical datasets and outperforms traditional classification models, including Naïve Bayes, Logistic Regression, Support Vector Machine (SVM), and Random Forest.

This study investigates the application of a hybrid Autoencoder-LSTM (AE-LSTM) model to improve the detection of Diabetic Nephropathy (DN) [28]. The autoencoder (AE) component compresses clinical data while preserving essential features and reducing dimensionality. In contrast, the Long Short-Term Memory (LSTM) network captures temporal dependencies and sequential patterns, thereby improving feature learning for early diagnosis. The dataset encompasses clinical and demographic variables, including age, sex, type of diabetes, disease duration, smoking habits, and alcohol consumption. Implemented in Python, the proposed model demonstrates superior performance compared to conventional methods. The hybrid AE-LSTM model achieves an accuracy of 99.2%, marking a 6.68% improvement over Random Forest (RF), Support Vector Machine (SVM), and Logistic Regression. These findings underscore the effectiveness of deep learning in accurately detecting DN at an early stage, providing a valuable tool for proactive disease

management in patients with diabetes.

This study presents an innovative approach to colon cancer diagnosis by integrating autoencoder-based feature selection, Capsule Networks (CapsNets), and histopathology images to address existing challenges [29]. CapsNets effectively capture spatial hierarchies in visual data, enhancing pattern recognition and classification accuracy. Autoencoders, when used for feature extraction, aid in dimensionality reduction, emphasise key features, and filter out noise, thereby improving overall model performance. The proposed method has achieved outstanding results, attaining an accuracy of 99.2%. The model's high accuracy in distinguishing malignant from non-malignant tissues underscores its ability to detect cancerous lesions with minimal errors. By combining auto encoders with Capsule Networks, this research marks a significant advancement in cancer detection, overcoming the limitations of conventional methods and providing a more reliable tool for early diagnosis.

This study introduces a versatile framework that utilises a lightweight Convolutional Neural Network (CNN) architecture to automate the diagnosis of lung and colon cancer in histopathological images across various diagnostic scenarios [30]. The commonly used LC25000 dataset, comprising 25,000 histopathological images classified into five categories—lung adenocarcinoma, lung squamous cell carcinoma, benign lung tissue, colon adenocarcinoma, and benign colonic tissue—serves as the foundation for this research. The study explores three diagnostic scenarios: (S1) differentiating between lung and colon samples, (S2) classifying benign and malignant images, and (S3) categorising into the five classes of the LC25000 dataset. The proposed model achieves exceptional performance across all scenarios, with accuracy, recall, precision, F1-score, and AUC exceeding 0.9947, 0.9947, and 0.9995, respectively. The lightweight CNN, with only 1.612 million parameters, proves to be highly efficient in automating the diagnosis of lung and colon cancer, outperforming several existing approaches.

This research presents an innovative chest X-ray classification framework that utilises a fine-tuned VGG19 model (16 layers) enhanced with Contrast Limited Adaptive Histogram Equalisation (CLAHE) for improved contrast, binary mask attention to emphasise abnormalities, and advanced data augmentation techniques for enhanced generalisation [31]. A key feature of this approach is the implementation of a Probabilistic U-Net for lung segmentation, which isolates critical features while employing weighted masks to focus on pathological regions. To address class imbalance, computed class weights are incorporated to ensure a fair learning process. The proposed method achieves an impressive 95% accuracy, along with superior class-specific performance metrics, surpassing existing deep learning techniques. In real-world healthcare applications, a test accuracy of 94.8% is achieved using various customised VGG19-based models, even without mask utilisation, demonstrating the model's robustness and interpretability.

This study introduces the Hierarchical Reinforcement Learning with Multi-Expert Feedback (ME-RL) framework, which aims to enhance automated disease diagnosis within dialogue systems [32]. The framework employs a hierarchical

structure with lower-level networks incorporating a reward model. In this setup, a discriminator, inspired by adversarial networks, evaluates the authenticity of symptom query sequences generated by the agent and provides rewards accordingly. Additionally, a large language model, reflecting human expert knowledge, assesses the appropriateness of the agent's current symptom queries, guiding the learning process of the policy network. This approach addresses data characteristic deficiencies and enhances the policy's ability to utilise feature information, thereby aligning the diagnostic process more closely with clinical practices. Experimental results demonstrate that the ME-RL framework achieves diagnostic success rates of 61.5% on synthetic datasets and 84.4% on real-world datasets, while also reducing the average number of dialogue turns required for diagnosis. These outcomes surpass those of conventional methods, indicating the framework's robust generalization capabilities.

This study [33] employs the Mask R-CNN semantic segmentation technique, which incorporates a ResNet-50 backbone, to analyse CT scans of COVID-19 patients. The model is trained on an annotated dataset, thereby enhancing its ability to segment and delineate the lung parenchyma in CT images accurately. Experimental results indicate that Mask R-CNN achieved a Dice Similarity Coefficient (DSC) of 93.4%, reflecting a high level of agreement between the segmented areas and clinically relevant regions. These findings underscore the effectiveness of the proposed approach in achieving precise lung tissue segmentation, facilitating quantitative assessments of lung impairments, and offering valuable insights for diagnosis and patient monitoring.

The study examines the effectiveness of combining various resampling techniques with machine learning algorithms to enhance prediction accuracy in imbalanced datasets for heart and lung diseases [34]. The authors integrate under-sampling methods, such as Edited Nearest Neighbours (ENN) and Instance Hardness Threshold (IHT), with oversampling techniques like Random Oversampling (RO), Synthetic Minority Oversampling Technique (SMOTE), and Adaptive Synthetic Sampling (ADASYN). These resampling strategies are paired with classifiers including Decision Trees (DT), Random Forests (RF), K-Nearest Neighbours (KNN), and Support Vector Machines (SVM). Model performance is evaluated using metrics such as accuracy, precision, recall, F1 score, and the Area Under the Curve (AUC). The results indicate that tailored resampling significantly enhances the performance of machine learning models in healthcare settings. Notably, SVM combined with ENN undersampling markedly improves accuracy for lung cancer predictions, while SVM and RF with IHT achieve higher validation accuracies for both diseases. Random oversampling exhibits variable effectiveness across datasets, whereas SMOTE and ADASYN consistently enhance accuracy.

Glaucoma, a primary cause of irreversible blindness, is characterised by distinct changes in the optic nerve head, also known as the optic disk. While manual assessments remain valuable, they are hindered by subjectivity, inconsistencies, and the significant time required for evaluation [35]. With the advent of artificial

intelligence, machine learning (ML) and deep learning (DL) models have emerged as powerful tools for automated and improved optic disk analysis. Convolutional Neural Networks (CNNs) have been at the forefront of DL advancements, with novel architectures enhancing both specificity and sensitivity. Additionally, hybrid models that combine traditional ML techniques with DL approaches have demonstrated increased robustness and generalizability. ML and DL technologies hold transformative potential in glaucoma diagnosis and management, offering a balance of accuracy, efficiency, and reliability. As these models continue to evolve by integrating larger datasets and multimodal imaging techniques, their clinical applications are expected to expand, fostering a stronger connection between technological progress and patient-centred care.

A neural network, a fundamental component of artificial intelligence, is designed to emulate the structure and function of the human brain [36]. It consists of interconnected nodes, or artificial neurons, organized into layers that process information sequentially. Each neuron receives inputs, performs computations, and transmits outputs to subsequent neurons. Through training on extensive datasets, neural networks adjust the weights of connections between neurons, thereby enhancing their ability to recognise patterns and make informed decisions. This adaptability has led to significant advancements in fields such as speech recognition, computer vision, and natural language processing. This paper offers a concise overview of various machine learning paradigms, application areas, different types of neural networks, and their respective applications.

This research contributes to ongoing efforts in cardiovascular disease (CVD) detection by utilising two powerful machine learning techniques: Multilayer Perceptron (MLP) and K-Nearest Neighbours (K-NN) [37]. The study employs publicly available data from the University of California, Irvine repository, refining model performance by eliminating outliers and attributes with null values. Experimental results indicate that the MLP model achieves a superior accuracy of 82.47% and an area under the curve (AUC) value of 86.41%, outperforming the KNN model. Therefore, the proposed MLP model is recommended as an effective solution for automated CVD detection.

The shift from traditional in-person classrooms to online learning environments has introduced challenges for both educators and students [38]. In virtual settings, instructors often focus on delivering content without real-time awareness of students' emotional states, which can lead to decreased engagement and increased feelings of fatigue and disinterest among learners. To address this issue, a prototype system has been developed to assist educators in evaluating students' behaviours and emotions during online sessions. This system employs facial detection technology to identify features such as the eyes, nose, and mouth, enabling the differentiation and detection of multiple faces. By integrating a Convolution Neural Network (CNN) trained to predict emotional states through facial expressions, the system aims to provide insights into students' affective behaviours, thereby enhancing the effectiveness of online education.

The authors [39] introduce a novel diagnostic framework that integrates a one-dimensional convolution neural network (CONV1D) with an enhanced long short-term memory

(LSTM) model. To assess data classification performance, confusion matrices are utilized within a deep learning algorithm. The proposed framework classifies data by incorporating key mechanical factors of bearings, such as sudden load variations, rotational speed, and operating temperature. This approach significantly enhances the model's training accuracy, achieving over 96.6%, with a percentage error of 23.29% after 50 iterations. Increasing the number of iterations could further improve accuracy, bringing it closer to 100% while reducing the error margin toward 0%.

Machine learning (ML) technology [40] identifies patterns associated with specific diseases by analysing extensive datasets containing patient records, including information on diabetes, blood pressure, cholesterol levels, X-rays, MRIs, CT scans, imaging data, and genomic information. ML algorithms assess key symptoms to determine disease presence. The effectiveness of these models relies on the availability of sufficient data and the selection of relevant features for computation. The performance and fairness of an ML model depend on the chosen features used to diagnose a disease. Selecting too many or too few features can lead to underfitting or overfitting, which in turn impact prediction accuracy. Ensuring all essential attributes are included while avoiding irrelevant ones is a challenging yet crucial aspect of model development. Omitting a key attribute or incorporating unrelated features can distort the model's outcomes. This research investigates the impact of feature selection and bias in ML disease prediction by employing Support Vector Machine (SVM) and Logistic Regression (LR) algorithms. The study emphasises the importance of careful feature selection in enhancing model reliability and fairness in disease diagnosis.

Early identification and management of various ocular diseases are crucial for improving patient outcomes, particularly in ophthalmology [41]. Recent studies have introduced innovative methods for predicting and classifying multiple eye conditions using ocular images, with a focus on assessing disease severity.

One approach employs a hybrid Convolutional Neural Network (CNN) architecture, consisting of two distinct CNN blocks, to classify images such as Optic Disc Cupping, Diabetic Retinopathy, Media Haze, and Healthy eyes. Utilizing the RFMiD dataset, this method extracts pertinent features from fundus images. To evaluate its efficacy, eight classification algorithms, viz. Gradient Boosting, Support Vector Machines, Voting Ensembles, various K-Nearest Neighbour (KNN) models, Naive Bayes, and Random Forest have been applied. Among these, the ensemble learning approach has achieved the highest accuracy of 93.39%, indicating the model's proficiency in distinguishing between different ocular conditions.

Another study [42] focused on classifying eye diseases using deep learning with CNNs enhanced by transfer learning. This research utilised a dataset comprising 4,217 images categorised into four classes: Normal (1,074 photos), Glaucoma (1,007 images), Cataract (1,038 images), and Diabetic Retinopathy (1,098 images). The CNN model, implemented in Tensor

Flow, demonstrated a high accuracy of 95%, with particularly notable performance in detecting Diabetic Retinopathy, achieving 100% precision and recall.

Furthermore, the application of transfer learning in CNNs [43] for multi-class classification of eye diseases has shown promising results. In one study, transfer learning has achieved an accuracy of 94%, surpassing the traditional CNN approach, which had an accuracy of 84%. This highlights the potential of transfer learning in improving the performance of deep learning models in ophthalmic diagnostics.

Collectively, these methodologies highlight the significant potential of advanced deep learning techniques, particularly CNNs and transfer learning, in the early detection and classification of various ocular diseases [44]. By leveraging large datasets of labelled ocular images, these approaches aim to improve diagnostic accuracy and facilitate timely interventions in ophthalmology.

This study [45] presents an innovative approach, named CADEYE, for classifying various ocular conditions, including diabetic retinopathy, hypertensive retinopathy, glaucoma, and contrast-related visual impairments. The method enhances diagnostic performance by combining features extracted from two deep learning models—MobileNet and EfficientNet—through feature fusion. To further boost accuracy, the system incorporates fluorescence imaging within its image processing workflow. Additionally, an interpretability-focused algorithm is integrated into the CADEYE system to improve explainability, marking a novel application of this algorithm in the context of eye disease diagnosis, as per the authors' assertion.

This research [46] introduces a deep learning-based approach for classifying eye diseases, emphasizing the use of digital image processing techniques to enhance the handling of ocular images. Specifically, blur filters have been applied to reduce noise, and the Canny edge detection algorithm has been utilized to delineate edges, facilitating the differentiation between various ocular conditions. Following pre-processing, a custom-designed Convolutional Neural Network (CNN) comprising 11 layers—including convolutional, max pooling, batch normalisation, flattening, and dense layers—has been employed for classification. The model has been trained and validated using the hold-out method with an 80–20 split. Evaluation metrics, including accuracy, precision, recall, F1-score, and a confusion matrix, have been used to assess the model's performance, with an overall efficiency of 97% across all metrics.

This research [47] presents a novel framework for classifying retinal eye diseases by combining Convolutional Neural Networks (CNNs) with Generative Adversarial Networks (GANs). Acknowledging the importance of precise diagnosis in ophthalmology, the approach utilizes CNNs for robust feature extraction and classification by capturing complex hierarchical patterns associated with different retinal disorders. In parallel, GANs are employed to produce synthetic retinal images, effectively expanding the dataset and mitigating challenges related to data scarcity and class imbalance often encountered in medical imaging.

This study [48] introduces a deep learning-based method for the automated classification of eye diseases. By training a model on a substantial dataset comprising images of both healthy and diseased eyes, the system learns to identify

distinguishing features and patterns associated with various ocular conditions. Once trained, the model can accurately categorize new eye images into predefined disease classes, facilitating prompt and precise diagnoses. Early detection of eye diseases is crucial, as timely intervention can prevent or mitigate the risk of vision loss and associated complications.

Early detection is crucial for halting the progression of many eye diseases, as timely diagnosis can prevent irreversible vision loss [49]. These conditions often manifest through a variety of visually observable symptoms, necessitating a comprehensive analysis for accurate identification. To address this, an innovative automated system is proposed that leverages digital image processing techniques—such as segmentation and morphological analysis—alongside deep learning methodologies, particularly convolutional neural networks (CNNs). This integrated approach aims to enhance the precision and efficiency of eye disease diagnosis by systematically evaluating the diverse visual indicators present in ocular images. By combining these advanced technologies, the model is designed to assist in the early detection of eye disorders, thereby facilitating prompt medical intervention and improving patient outcomes.

In deep learning-based eye recognition, transfer learning is employed to fine-tune the network [50], enhancing the model's learning efficiency. To reduce decision bias and increase the reliability of diagnostic outcomes, a decision fusion model based on Dempster-Shafer (D-S) theory is introduced. However, since traditional D-S theory often encounters issues with incompleteness and conflicts, an enhanced version—Improved Dempster-Shafer Evidence Theory (ID-SET) is proposed to resolve these paradoxes. This improved method is then applied to the decision fusion process within eye disease recognition models to ensure more credible and consistent results.

This study [51] focuses on enhancing the automated classification of ocular diseases by leveraging advanced deep learning architectures, specifically Convolutional Neural Networks (CNNs), DenseNet-121, and Xception. DenseNet121 is characterised by its densely connected layers, which facilitate improved gradient flow and feature propagation. At the same time, Xception utilises depth-wise separable convolutions to extract intricate features from retinal images efficiently. In addition to these deep learning models, traditional machine learning classifiers such as Random Forest and Support Vector Machine (SVM) are incorporated to evaluate and potentially integrate their outputs. Random Forest, an ensemble learning method, constructs multiple decision trees to enhance predictive accuracy and mitigate overfitting. This hybrid framework has demonstrated significant potential in improving diagnostic accuracy for ocular diseases. For instance, studies have reported that the DenseNet121 model achieved an accuracy of 97.30% in detecting diabetic retinopathy, outperforming other approaches. This study aims to develop a deep learning (DL) system capable of efficiently and accurately detecting intraocular tumours (IOT), retinal detachments (RD), vitreous haemorrhages (VH), and posterior scleral staphylomas (PSS) using

ocular B-scan ultrasound images [52]. The proposed system utilises ultrasound images from five clinically validated categories—vitreous haemorrhage, retinal detachment, intraocular tumour, posterior scleral staphyloma, and healthy eyes—to train and assess a fine-grained classification model
Summary of Literature Review is as Follows: -

Table-I: Methods used and the Objective of the Paper by the Authors in the Literature Review

| Paper No | Methods | Key Finding |
|----------|--|--|
| 1 | Machine Learning models | Health care(oral) disease prediction with an objective of recovery |
| 2, 4, 6 | Machine Learning models | Healthcare disease prediction with the objective of recovery. |
| 5 | Machine Learning models using gene expression data | Lung cancer detection & recovery. |
| 7 | Ensemble Techniques | Heart disease detection & recovery |
| 9 | Segmentation & deep learning techniques | Health care disease prediction with an objective of recovery |
| 10 | CNN and LSTM models with ECG signals | Health care disease prediction with an objective of recovery |
| 11 | CNN models | Heart disease prediction with an objective of recovery |
| 12 | Machine Learning models | Breast Cancer detection & recovery. |
| 13 | LSTM, CNN models | Breast Cancer detection & recovery |
| 14 | Segmentation | Lung cancer prediction using CT scan images |
| 15 | CNN + RELU algorithms | The BraTS2020 dataset is used for detecting brain tumours. |
| 16 | Deep learning models | Cardiac abnormalities detection. |
| 17 | Machine learning models | Cancer prediction |
| 18 | Mobile Net, CNN models, viz. VGG16, Xception, Resnet50 | Brain tumour prediction. |
| 19 | Machine Learning models | Diabetics prediction |
| 20 | InceptionV3 model | Brain tumour prediction |
| 21 | CNN | Diabetic Retinopathy Prediction |
| 22, 25 | Deep learning models | Heart disease prediction |
| 23 | Deep learning, transfer learning, hybrid models | Pneumonia detection |
| 24 | Deep CNN | Chronic kidney disease prediction |
| 26 | Deep learning models | Lung disease detection |
| 28 | Hybrid Auto encoder& LSTM | Diabetics prediction |
| 29 | Autoencoder with a Capsule Network | Colon cancer prediction |
| 30 | Lightweight CNN | Colon cancer prediction |
| 31 | CNN | Chest disease prediction |
| 33 | Segmentation mask RCNN with ResNet 50 | Lung disease detection |
| 35 | Machine learning, Deep learning models | Lung disease detection& recovery |
| 37 | Machine learning models | Cardiovascular disease prediction |
| 38 | CNN and LSTM | Prediction of students' emotions in class |
| 41 | Deep learning algorithms | Eye disease prediction |
| 42 | Fundus Image Classification | Retinal Disease |
| 43 | Deep learning Convolution Neural Network | Eye Disease Classification |
| 44 | Deep learning Techniques | Eye Disease Classification |
| 45 | Multi-Eye Disease Classification | Feature Fusion with Deep Learning Models and Fluorescence Imaging |
| 46 | Deep Learning models | Identification of Eye Disease |
| 47 | Deep Learning models | Retinal disease classification |
| 48 | Deep learning classification using a convolutional neural network | Eye Disease Classification |
| 49 | Deep learning models | Identification of Eye Disease |
| 50 | Deep learning models (Convolution Neural Network) | Eye Disease Classification |
| 51 | Deep learning models (Convolutional Neural Networks (CNNs), DenseNet121, and Xception) | Eye Disease Classification |
| 52 | Deep learning models | Ocular disease detection |

III. MOTIVATION

A significant amount of research has been conducted in the field of healthcare prediction to detect illnesses in various organs. Machine learning algorithms have also been proposed in ([1], [2], [4], [5], [6], [12], [17], [19], [37], [42], [46], [48], [52]). Deep Learning models have been proposed in ([9], [16], [22], ([24], [25], [26], [41], [43], [44], [45], [46], [47], [48], [49], [50], [51], [52]). Segmentation has been done in ([9], [14], [33]). However, no author has worked on the same data set and has not evaluated several evaluation measures. This is the reason for the proposed work presented in this paper. Here, an effort is being made to utilise deep learning models [55] on a retinal eye image disease dataset, to select a particular model suitable for analysing the dataset. After choosing an appropriate model, it is necessary to identify the individuals affected by the disease, so that, over time, the

known as the Dual-Path Lesion Attention Network (DPLA-Net). Machine Learning models have been used for predicting and eliminating software programs [53]. Prediction of orthopaedic disease has been utilized using soft computing models [54].

concerned individuals may recover with the application of proper medication, food, and other essential items as needed.

IV. DATA SET

The retinal fundus image dataset has been collected from the Kaggle Repository ([13]). A retinal fundus image, also known as a fundus photograph, is a picture of the back of the eye, specifically the inner surface, which includes the retina, macula, optic disc, and blood vessels. It helps eye care professionals diagnose and monitor various eye conditions and diseases. The term "fundus" refers to the back, inner surface of the eye, where the retina is located.

The image data set comprises training, testing, and validation datasets. Each image data set



includes 11 types. These are furnished below: -

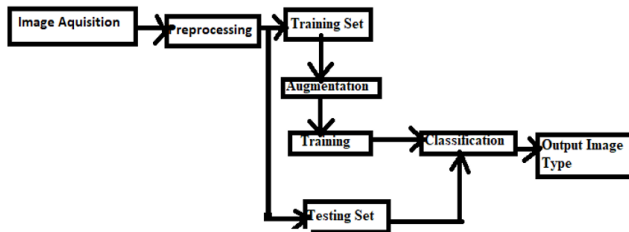
Table-II: Retina Fundus Image Data Set

| No | Image type | Image-related Information |
|----|--------------------------|--|
| 1 | Dry AMD | Age-Related Macular Degeneration Diagnosis |
| 2 | Wet AMD | Age-Related Macular Degeneration Diagnosis |
| 3 | Mild DR | Mild diabetic retinopathy (DR) |
| 4 | Moderate DR | Moderate diabetic retinopathy (DR) |
| 5 | Severe DR | Severe diabetic retinopathy (DR) |
| 6 | Proliferate DR | Rapidly growing cells in diabetic retinopathy (DR) |
| 7 | Cataract | based on the severity of the opacity and its impact on vision. |
| 8 | Hypertensive Retinopathy | narrowing of arteries in the retina, thickening of the arterioles' walls, and potentially other signs like haemorrhages, exudates, and optic disc swelling |
| 9 | Pathological Myopia | Related to the decaying change in the Retina |
| 10 | Glaucoma | Glaucoma fundus images, or retinal images taken to assess the optic nerve head, can reveal various characteristics of glaucoma. These images are crucial for diagnosing and monitoring glaucoma, a leading cause of blindness. |
| 11 | Normal Fundus | A normal fundus image, captured via fundus photography, typically shows the back of the eye with a healthy-looking retina, optic disc, and blood vessels. |

V. METHODOLOGY

A. Custom Convolution Neural Network:

A Convolutional Neural Network-based architecture is being developed to efficiently detect and classify eye diseases. The block diagram of the proposed methodology is shown in Figure 1. The pre-processing step of the method involves cropping the images to remove unwanted backgrounds and resizing all images to a fixed size of 256 x 256 pixels. Following the pre-processing step, each class of the dataset is randomly split into an 80:20 proportion for training and testing. Then, the training samples are augmented to increase the number of images before the training process.

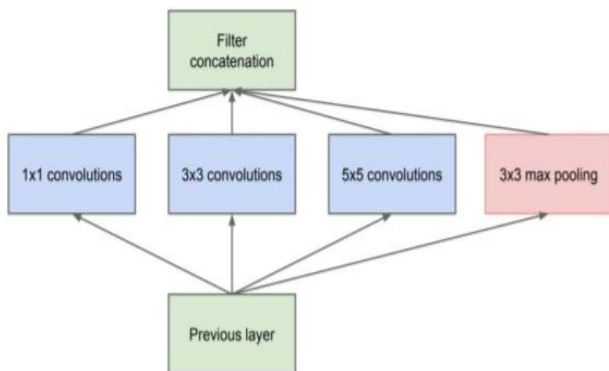


[Fig.1: Convolution Neural Network]

B. Inception V3:

The Inception Network (ResNet) is a well-known deep learning model, as illustrated in Figures 2 and 3.

▪ Inception Module (Naive)

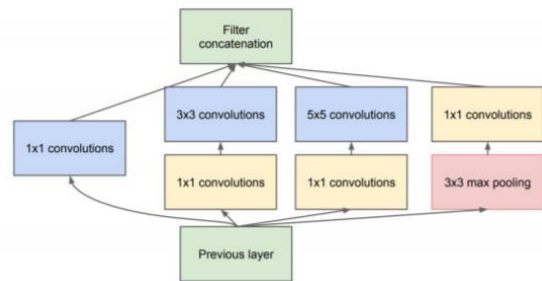


[Fig.2: Inception V3]

Process visual/spatial information at various scales and then

aggregate. This is computationally. Optimistic and 5x5 convolutions are especially expensive.

C. Inception Module (Dimension Reduction):



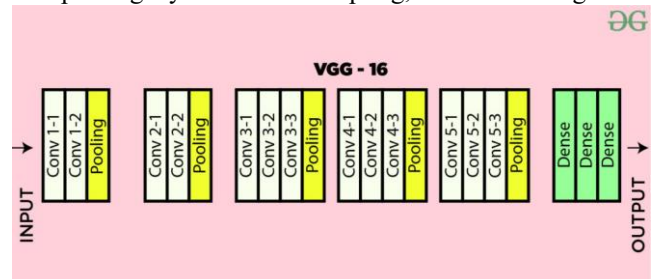
[Fig.3: Inception Module (Dimension Reduction)]

Using the inception module, a dimension-reduced inception module, a deep neural network architecture was built (Inception v1).

The popular versions of the Inception network are Inception v1, Inception v2, Inception v3, Inception v4, and Inception-ResNet.

D. VGG-16:

The VGG-16 configuration typically consists of 16 layers, including 13 convolutional layers and three fully connected layers. These layers are organised into blocks, with each block containing multiple convolutional layers followed by a max-pooling layer for downsampling, as shown in Figure 4.



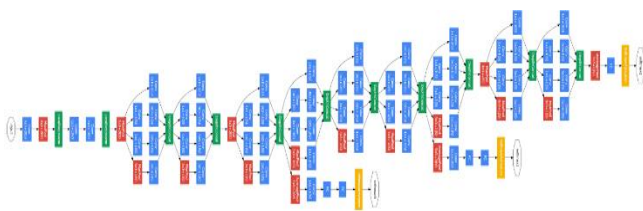
[Fig.4: VGG 16]

The VGG-16 model is a convolutional neural network (CNN) architecture. It is characterised by its depth, comprising 16 layers, including 13 convolutional layers and three fully

connected layers. VGG-16 is renowned for its simplicity and effectiveness, as well as its ability to achieve strong performance on various computer vision tasks, including image classification and object recognition. The model's architecture features a stack of convolution layers followed by max-pooling layers, with progressively increasing depth. This design enables the model to learn intricate hierarchical representations of visual features, leading to robust and accurate predictions.

E. GoogleNet:

Inception architecture utilises CNN blocks multiple times with different filters, such as 1×1 , 3×3 , and 5×5 , etc. Therefore, let us create a class for the CNN block, which takes input channels and output channels, along with batch normalisation (BatchNorm2d) and ReLU activation, as shown in Figure 5.



[Fig.5: Google Net]

F. Features of GoogleNet:

The GoogleNet architecture is significantly different from previous state-of-the-art architectures, such as AlexNet and ZF-Net. It employs various methods, such as 1×1 convolution and global average pooling, which enable it to create a deeper architecture. In the architecture, we will discuss some of these methods:

1×1 convolution: The inception architecture uses 1×1 convolution in its architecture. These convolutions are used to decrease the number of parameters (weights and biases) of the architecture. By reducing the parameters, the depth of the architecture can be increased.

G. MobileNet:

MobileNetV2 is a convolutional neural network architecture optimized for mobile and embedded vision applications. It improves upon the original MobileNet by introducing inverted residual blocks and linear bottlenecks, resulting in higher accuracy and speed while maintaining low computational costs.

Key Features of MobileNet V2

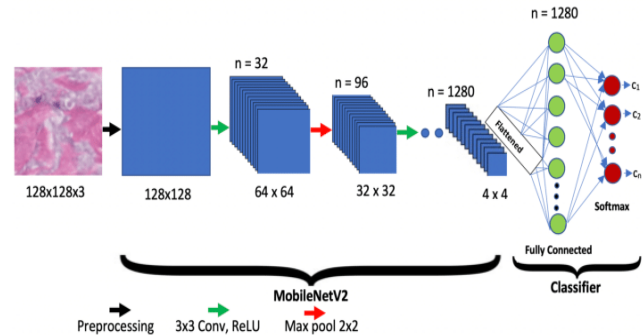
Inverted Residuals: One of the most notable features of MobileNet V2 is the use of inverted residual blocks. Unlike traditional residual blocks that connect layers of the same depth, inverted residuals connect layers with different depths, allowing for more efficient information flow and reducing computational complexity.

Linear Bottlenecks: MobileNet V2 introduces linear bottlenecks between the layers. These bottlenecks help preserve the information by maintaining low-dimensional representations, which minimizes information loss and improves the overall accuracy of the model.

Depthwise Separable Convolutions: Similar to MobileNet V1, MobileNet V2 employs depthwise separable convolutions to reduce the number of parameters and

computations. This technique splits the convolution into two separate operations: depthwise convolution and pointwise convolution, significantly reducing computational cost.

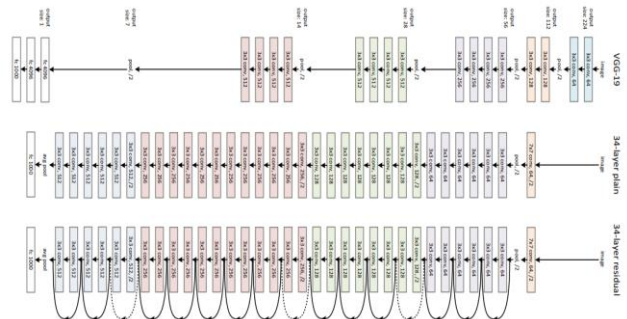
ReLU6 Activation Function: MobileNet V2 utilises the ReLU6 activation function, which clips the ReLU output at a value of 6. This helps prevent numerical instability in low-precision computations, making the model more suitable for mobile and embedded devices.



[Fig.6: Mobile Net V2]

H. Res Net:

Many Residual blocks are stacked together to form a ResNet, as shown in Figure 7. The idea is to connect the input of a layer directly to the output of a subsequent layer, skipping a few intermediate connections. This network employs a 34-layer plain network architecture inspired by VGG-19, to which a shortcut connection is then added. These shortcut connections then convert the architecture into a residual network.

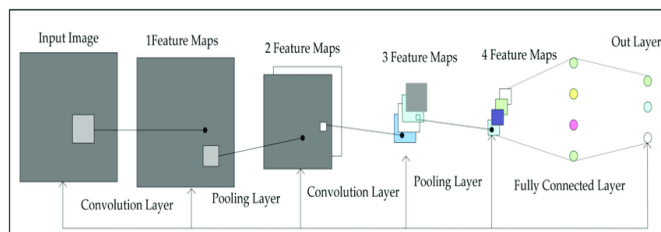


[Fig.7: Res Net]

I. Dense Net 121:

DenseNet, also known as a Dense Convolutional Network, is a deep learning architecture for convolutional neural networks (CNNs). DenseNet revolutionized the field of computer vision by proposing a novel connectivity pattern within CNNs, addressing challenges such as feature reuse, vanishing gradients, and parameter efficiency. Unlike traditional CNN architectures, where each layer is connected only to subsequent layers, DenseNet establishes direct connections between all layers within a block. This dense connectivity enables each layer to receive feature maps from all preceding layers as inputs, fostering extensive information flow throughout the network.

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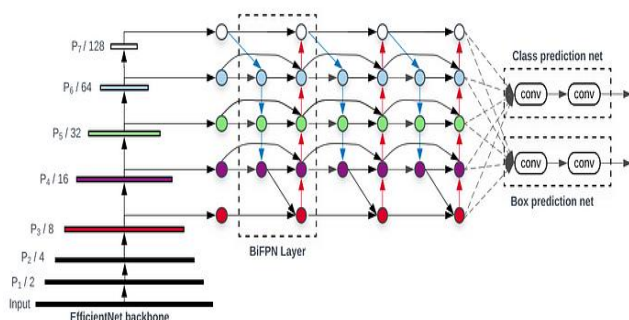


[Fig.8: Dense Net 121]

J. Efficient Net B2:

EfficientNet is a group of convolutional network models that have achieved state-of-the-art accuracy in the ImageNet database with a very few parameters compared to other models competing in ImageNet. The efficient model group comprises eight models, ranging from B0 to B7, where each model is chronologically associated with higher accuracy and a larger number of parameters.

This model emphasises keeping the number of parameters low while increasing accuracy. To achieve this, it utilises depthwise separable convolution and pointwise convolution, which were introduced in Mobile ConvNet. The following picture provides an overview of depthwise convolution, as illustrated in Figure 9. EfficientNet B2 is a specific variant of the EfficientNet family of deep learning models. Efficient Net B2 models are designed to achieve high accuracy with limited computational resources, making them suitable for deployment on edge devices or in applications where efficiency is crucial.



[Fig.9: Efficient Net]

VI. PROPOSED FLOW OF WORK

Step 1. Data Collection. The Retinal Eye Dataset have been collected from

Step 2. The dataset containing relevant information for predicting eye disease has been collected.

Step 3. The data have been entered accurately and completely.

Step 4. Data Pre-processing: Data cleaning and outlier removal have been performed.

Step 5. Taking care of missing data by inputting specific, concerned data or removing that data based on the nature and quantity of missing values.

Step 6. Cleaning the data by tackling inconsistencies, errors, and anomalies.

Step 7. Detection and removal of outliers that may affect the analysis.

Step 8. Implementation of Deep Learning models and Performance Evaluation:

Step 9. Under deep learning classifier models, the following custom convolutional neural network models are used: Custom Convolutional Neural Network, Inception V3, VGG16, GoogleNet, MobileNet, ResNet, DenseNet-121, and EfficientNet-B2.

Step 10. Train the classifiers using the pre-processed data.

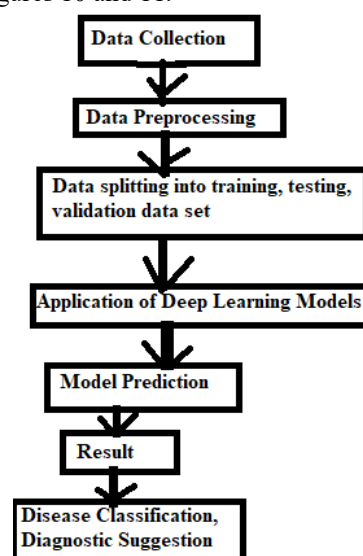
Step 11. Evaluate the performance of each classifier using evaluation metrics like accuracy, precision, recall, and F1 score.

Step 12. Identify the most accurate and reliable method for predicting the retinal eye disease based on the results obtained.

A. Classification

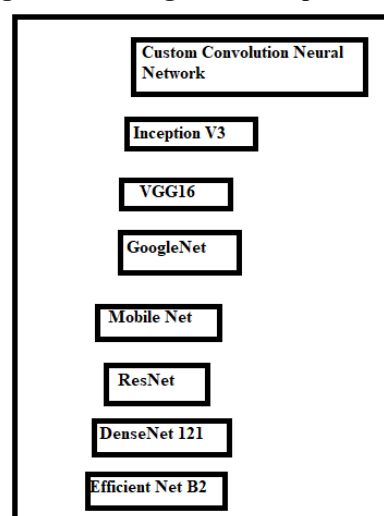
i. Application of Deep Learning models.

The application of deep learning models has been applied to input data. The application of deep learning models is shown in Figures 10 and 11.



Flow Diagram of proposed steps

[Fig.10, Flow Diagram of Proposed Steps]



[Fig.11: Application of Deep Learning Models]

B. Custom Convolution Neural Network (Custom CNN)

The available data must be preprocessed and applied to a Custom Convolutional Neural Network (Custom CNN). The training of the Custom CNN is as follows: -

Epoch 1/10

3/3 229s 111s/step - accuracy: 0.4368 - loss: 1.3380 - Val accuracy: 0.0693

- val_loss: 37.6038

Epoch 2/10

3/3 10s 4s/step - accuracy: 1.0000 - loss: 0.0000e+00 - Val accuracy: 0.0693

- val_loss: 62.1778

Epoch 3/10

3/3 10s 5s/step - accuracy: 1.0000 - loss: 0.0000e+00 - Val accuracy: 0.0693

- val_loss: 81.4219

Epoch 4/10

3/3 11s 4s/step - accuracy: 1.0000 - loss: 0.0000e+00 - Val accuracy: 0.0693

- val_loss: 96.9629

Epoch 5/10

3/3 20s 4s/step - accuracy: 1.0000 - loss: 0.0000e+00 - Val accuracy: 0.0693

- val_loss: 109.5313

Epoch 6/10

3/3 9s 4s/step - accuracy: 1.0000 - loss: 0.0000e+00 - Val accuracy: 0.0693

- val_loss: 119.5889

Epoch 7/10

3/3 10s 4s/step - accuracy: 1.0000 - loss: 0.0000e+00 - Val accuracy: 0.0693

- val_loss: 127.5427

Epoch 8/10

3/3 13s 6s/step - accuracy: 1.0000 - loss: 0.0000e+00 - Val accuracy: 0.0693

- val_loss: 133.7806

Epoch 9/10

3/3 17s 4s/step - accuracy: 1.0000 - loss: 0.0000e+00 - Val accuracy: 0.0693

- val_loss: 138.6358

Epoch 10/10

3/3 10s 5s/step - accuracy: 1.0000 - loss: 0.0000e+00 - Val accuracy: 0.0693

- val_loss: 142.3897

<keras.src.callbacks.history.History at 0x78d6d8139810>

The accuracy is 97% and the loss is 0%.

The classification report is as follows: -

Classification Report:

Precision, recall, f1-score, support

| | | | | |
|----|------|------|------|----|
| 0 | 0.07 | 1.00 | 0.13 | 30 |
| 1 | 0.00 | 0.00 | 0.00 | 44 |
| 2 | 0.00 | 0.00 | 0.00 | 54 |
| 3 | 0.00 | 0.00 | 0.00 | 19 |
| 4 | 0.00 | 0.00 | 0.00 | 42 |
| 5 | 0.00 | 0.00 | 0.00 | 90 |
| 6 | 0.00 | 0.00 | 0.00 | 49 |
| 7 | 0.00 | 0.00 | 0.00 | 30 |
| 8 | 0.00 | 0.00 | 0.00 | 24 |
| 9 | 0.00 | 0.00 | 0.00 | 30 |
| 10 | 0.00 | 0.00 | 0.00 | 21 |

| | | | | |
|--------------|------|------|------|-----|
| accuracy | | | 0.07 | 433 |
| macro avg | 0.01 | 0.09 | 0.01 | 433 |
| weighted avg | 0.00 | 0.07 | 0.01 | 433 |

The Confusion matrix is as follows: -

Confusion Matrix:

| | | | | | | | | | | |
|-----|---|---|---|---|---|---|---|---|---|----|
| [30 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0] |
| [44 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0] |
| [54 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0] |
| [19 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0] |
| [42 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0] |
| [90 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0] |
| [49 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0] |

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```
[30 0 0 0 0 0 0 0 0 0 0]
[24 0 0 0 0 0 0 0 0 0 0]
[30 0 0 0 0 0 0 0 0 0 0]
[21 0 0 0 0 0 0 0 0 0 0]
```

C. Inception V3

The available data has to be preprocessed and applied to Inception V3. The training of Inception V3 is as follows: -

```
/usr/local/lib/python3.11/dist-packages/keras/src/trainers/data_adapters/py_dataset_adapter.py:121: UserWarning: Your
'PyDataset' class should call 'super (). __init__(**kwargs)' in its constructor. '**kwargs' can include 'workers',
'use_multiprocessing', and 'max_queue_size'. Do not pass these arguments to 'fit () ', as they will be ignored.
```

```
self._warn_if_super_not_called()
```

Epoch 1/20

```
3/3-----4841s 2409s/step - accuracy: 0.7300 - loss: 0.3581 - val_accuracy:
0.0049 - val_loss: 265.5146
```

Epoch 2/20

```
3/3-----47s 23s/step - accuracy: 1.0000 - loss: 1.1708e-10 - val_accuracy: 0.0049
- val_loss: 397.1148
```

Epoch 3/20

```
3/3-----48s 23s/step - accuracy: 1.0000 - loss: 3.9627e-15 - val_accuracy: 0.0049
- val_loss: 487.2628
```

Epoch 4/20

```
3/3-----47s 23s/step - accuracy: 1.0000 - loss: 2.6640e-18 - val_accuracy: 0.0049
- val_loss: 552.8154
```

Epoch 5/20

```
3/3-----48s 24s/step - accuracy: 1.0000 - loss: 6.1177e-20 - val_accuracy: 0.0049
- val_loss: 601.6600
```

Epoch 6/20

```
3/3-----46s 23s/step - accuracy: 1.0000 - loss: 1.7506e-21 - val_accuracy: 0.0049
- val_loss: 638.4747
```

The accuracy is 94%.

The classification report is as follows: -

| | precision | recall | f1-score | support |
|-------------------|-----------|--------|----------|---------|
| 3. Mild DR | 1.00 | 0.94 | 0.97 | 17 |
| 6. Proliferate DR | 0.00 | 0.00 | 0.00 | 0 |
| accuracy | | | 0.94 | 17 |
| macro avg | 0.50 | 0.47 | 0.48 | 17 |
| weighted avg | 1.00 | 0.94 | 0.97 | 17 |

Confusion matrix is as follows: -

```
array([[16, 1],
       [ 0, 0]])
```

D. VGG16

The available data has to be preprocessed and applied to VGG16. The training of VGG16 is as follows: -

Found 85 images belonging to 11 classes.

Found 1311 images belonging to 12 classes.

Found 6145 images belonging to 13 classes.

Epoch 1/10

```
3/3-----952s 475s/step - accuracy: 0.5274 - loss: 1.4198 - val_accuracy: 0.0049
- val_loss: 18.2741
```

Epoch 2/10

```
3/3-----42s 21s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy:
0.0049 - val_loss: 27.6944
```

Epoch 3/10

```
3/3-----40s 20s/step - accuracy: 1.0000 - loss:
0.0000e+00 - val_accuracy: 0.0049 - val_loss: 33.8980
```

Epoch 4/10

3/3-----41s 20s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 0.0049 - val_loss: 38.2923
Epoch 5/10
3/3-----41s 20s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 0.0049 - val_loss: 41.5070
Epoch 6/10
3/3-----41s 20s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 0.0049 - val_loss: 43.8978
Epoch 6: early stopping
The accuracy is 0%.
The classification report is as follows: -

41/41-----28s 681ms/step

| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0 | 0.00 | 0.00 | 0.00 | 1311.0 |
| 11 | 0.00 | 0.00 | 0.00 | 0.0 |
| accuracy | | | 0.00 | 1311.0 |
| macro avg | 0.00 | 0.00 | 0.00 | 1311.0 |
| weighted avg | 0.00 | 0.00 | 0.00 | 1311.0 |

The confusion matrix is as follows: -
[[0 1311]
[0 0]]

E. GoogleNet

The available data has to be preprocessed and applied to GoogleNet. The training of GoogleNet is as follows: -

Epoch 1/10
2/2-----394s 367s/step - accuracy: 0.2642 - loss: 2.2087 - val_accuracy: 0.0697
- val_loss: 28.9705
Epoch 2/10
1/2-----0s 100ms/step - accuracy: 1.0000 - loss: 0.0000e+00
/usr/local/lib/python3.11/dist-packages/keras/src/trainers/epoch_iterator.py:107: UserWarning: Your input ran out of data; interrupting training. Make sure that your dataset or generator can generate at least `steps_per_epoch * epochs` batches. You may need to use the `repeat()` function when building your dataset.
self._interrupted_warning()
2/2-----27s 27s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 0.0721 - val_loss: 38.3803
Epoch 3/10
2/2-----4s 4s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 0.0697
- val_loss: 53.7530
Epoch 4/10
2/2-----3s 3s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 0.0673
- val_loss: 60.2406
Epoch 5/10
2/2-----5s 5s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 0.0721
- val_loss: 70.7773
Epoch 6/10
2/2-----3s 3s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 0.0697
- val_loss: 75.4770
Epoch 7/10
2/2-----5s 4s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 0.0697
- val_loss: 83.2164
Epoch 8/10
2/2-----5s 5s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 0.0721
- val_loss: 86.2199
Epoch 9/10
2/2-----5s 5s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 0.0697 - val_loss: 92.6296
Epoch 10/10

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2/2-----3s 3s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 0.0721
 - val_loss: 94.8750
 <keras.src.callbacks.history.History at 0x7e5397d6c790>
 The accuracy is 14%. The classification report is as follows: -
 Classification Report

| | precision | recall | f1-score | support |
|------------------------|-----------|--------|----------|---------|
| 1. Dry AMD | 1.00 | 0.14 | 0.25 | 85 |
| 10. Glaucoma | 0.00 | 0.00 | 0.00 | 0 |
| 11. Normal Fundus | 0.00 | 0.00 | 0.00 | 0 |
| 5. Severe DR | 0.00 | 0.00 | 0.00 | 0 |
| 6. Proliferate DR | 0.00 | 0.00 | 0.00 | 0 |
| 7. Cataract | 0.00 | 0.00 | 0.00 | 0 |
| 9. Pathological Myopia | 0.00 | 0.00 | 0.00 | 0 |
| accuracy | | | 0.14 | 85 |
| macro avg | 0.14 | 0.02 | 0.04 | 85 |
| weighted avg | 1.00 | 0.14 | 0.25 | 85 |

Confusion Matrix is as Follows: -

Confusion Matrix
 [[12 1 8 7 1 2 54]
 [0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0]]

F. Mobile Net

The available data has to be preprocessed and applied to MobileNet. The training of MobileNet is as follows: -

Epoch 1/10

2/2-----143s 130s/step - accuracy: 0.2083 - loss: 2.2510 - val_accuracy: 0.0673
 - val_loss: 3.0523

Epoch 2/10

1/2-----0s 814ms/step - accuracy: 1.0000 - loss: 0.8100

/usr/local/lib/python3.11/dist-packages/keras/src/trainers/epoch_iterator.py:107: UserWarning: Your input ran out of data; interrupting training. Make sure that your dataset or generator can generate at least `steps_per_epoch * epochs` batches. You may need to use the `repeat()` function when building your dataset.

self.interrupted_warning()

2/2-----25s 24s/step - accuracy: 1.0000 - loss: 0.8100 - val_accuracy: 0.0697 -
 val_loss: 3.6421

Epoch 3/10

2/2-----67s 22s/step - accuracy: 1.0000 - loss: 0.2969 - val_accuracy: 0.0721 -
 val_loss: 5.0933

Epoch 4/10

2/2-----23s 22s/step - accuracy: 1.0000 - loss: 0.0480 - val_accuracy: 0.0697 -
 val_loss: 5.8025

Epoch 5/10

2/2-----61s 26s/step - accuracy: 1.0000 - loss: 0.0205 - val_accuracy: 0.0721 -
 val_loss: 6.9492

Epoch 6/10

2/2-----39s 38s/step - accuracy: 1.0000 - loss: 0.0096 - val_accuracy: 0.0721 -
 val_loss: 7.4664

Epoch 7/10

2/2-----42s 24s/step - accuracy: 1.0000 - loss: 0.0028 - val_accuracy: 0.0673 -
 val_loss: 8.3762

Epoch 8/10

2/2-----41s 40s/step - accuracy: 1.0000 - loss:
 0.0013 - val_accuracy: 0.0625 - val_loss: 8.7886

Epoch 9/10

2/2-----41s 24s/step - accuracy: 1.0000 - loss: 0.0013 - val_accuracy: 0.0697 - val_loss: 9.3749

Epoch 10/10

2/2-----41s 40s/step - accuracy: 1.0000 - loss: 7.1281e-04 - val_accuracy: 0.0721 - val_loss: 9.6602

<keras.src.callbacks.history.History at 0x7f7698052c50>

The accuracy is 7%. The classification report is as follows: -

Classification Report

| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0 | 0.07 | 1.00 | 0.13 | 30 |
| 1 | 0.00 | 0.00 | 0.00 | 44 |
| 2 | 0.00 | 0.00 | 0.00 | 54 |
| 3 | 0.00 | 0.00 | 0.00 | 19 |
| 4 | 0.00 | 0.00 | 0.00 | 42 |
| 5 | 0.00 | 0.00 | 0.00 | 90 |
| 6 | 0.00 | 0.00 | 0.00 | 49 |
| 7 | 0.00 | 0.00 | 0.00 | 30 |
| 8 | 0.00 | 0.00 | 0.00 | 24 |
| 9 | 0.00 | 0.00 | 0.00 | 30 |
| 10 | 0.00 | 0.00 | 0.00 | 21 |
| accuracy | | | 0.07 | 433 |
| macro avg | 0.01 | 0.09 | 0.01 | 433 |
| weighted avg | 0.00 | 0.07 | 0.01 | 433 |

The Confusion matrix is as follows: -

Confusion Matrix:

```
[[30  0  0  0  0  0  0  0  0  0  0]
 [44  0  0  0  0  0  0  0  0  0  0]
 [54  0  0  0  0  0  0  0  0  0  0]
 [19  0  0  0  0  0  0  0  0  0  0]
 [42  0  0  0  0  0  0  0  0  0  0]
 [90  0  0  0  0  0  0  0  0  0  0]
 [49  0  0  0  0  0  0  0  0  0  0]
 [30  0  0  0  0  0  0  0  0  0  0]
 [24  0  0  0  0  0  0  0  0  0  0]
 [30  0  0  0  0  0  0  0  0  0  0]
 [21  0  0  0  0  0  0  0  0  0  0]]
```

G. ResNet.

The available data has to be preprocessed and applied to ResNet. The training of ResNet is as follows: -

Epoch 1/10

2/2-----173s 152s/step - accuracy: 0.2642 - loss: 2.2347 - val_accuracy: 0.0721 - val_loss: 7.6576

Epoch 2/10

1/2-----4s 5s/step - accuracy: 1.0000 - loss: 0.0030

/usr/local/lib/python3.11/dist-packages/keras/src/trainers/epoch_iterator.py:107: UserWarning: Your input ran out of data; interrupting training. Make sure that your dataset or generator can generate at least `steps_per_epoch * epochs` batches. You may need to use the `repeat()` function when building your dataset.

self._interrupted warning()

2/2-----82s 77s/step - accuracy: 1.0000 - loss: 0.0030 - val_accuracy: 0.0673 - val_loss: 10.1861

Epoch 3/10

2/2-----89s 82s/step - accuracy: 1.0000 - loss: 1.7846e-04 - val_accuracy: 0.0721

- val_loss: 13.7478

Epoch 4/10

2/2-----82s 75s/step - accuracy: 1.0000 - loss:

5.7779e-06 - val accuracy: 0.0673 - val_loss: 15.2444

Epoch 5/10

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```
2/2-----146s 108s/step - accuracy: 1.0000 - loss: 7.5728e-07 - val_accuracy:
0.0697 - val_loss: 17.5114
Epoch 6/10
2/2-----83s 77s/step - accuracy: 1.0000 - loss: 6.3330e-08 - val_accuracy: 0.0721
- val_loss: 18.4337
Epoch 7/10
2/2-----98s 87s/step - accuracy: 1.0000 - loss: 1.0175e-08 - val_accuracy: 0.0649
- val_loss: 20.1994
Epoch 8/10
2/2-----141s 134s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy:
0.0721 - val_loss: 20.7453
Epoch 9/10
2/2-----89s 83s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy:
0.0673 - val_loss: 22.0804
Epoch 10/10
2/2-----82s 76s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy:
0.0673 - val_loss: 22.5718
```

<keras.src.callbacks.history.History at 0x7f3494494c10>

The accuracy is 7 %. The classification report is as follows: -

Classification Report

| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0 | 0.07 | 1.00 | 0.13 | 30 |
| 1 | 0.00 | 0.00 | 0.00 | 44 |
| 2 | 0.00 | 0.00 | 0.00 | 54 |
| 3 | 0.00 | 0.00 | 0.00 | 19 |
| 4 | 0.00 | 0.00 | 0.00 | 42 |
| 5 | 0.00 | 0.00 | 0.00 | 90 |
| 6 | 0.00 | 0.00 | 0.00 | 49 |
| 7 | 0.00 | 0.00 | 0.00 | 30 |
| 8 | 0.00 | 0.00 | 0.00 | 24 |
| 9 | 0.00 | 0.00 | 0.00 | 30 |
| 10 | 0.00 | 0.00 | 0.00 | 21 |
| accuracy | | | 0.07 | 433 |
| macro avg | 0.01 | 0.09 | 0.01 | 433 |
| weighted avg | 0.00 | 0.07 | 0.01 | 433 |

The confusion matrix is as follows: -

Confusion Matrix

```
[[30  0  0  0  0  0  0  0  0  0  0]
 [44  0  0  0  0  0  0  0  0  0  0]
 [54  0  0  0  0  0  0  0  0  0  0]
 [19  0  0  0  0  0  0  0  0  0  0]
 [42  0  0  0  0  0  0  0  0  0  0]
 [90  0  0  0  0  0  0  0  0  0  0]
 [49  0  0  0  0  0  0  0  0  0  0]
 [30  0  0  0  0  0  0  0  0  0  0]
 [24  0  0  0  0  0  0  0  0  0  0]
 [30  0  0  0  0  0  0  0  0  0  0]
 [21  0  0  0  0  0  0  0  0  0  0]]
```

H. DenseNet 121.

The available data must be preprocessed and applied to DenseNet-121. The training of DenseNet121 is as follows: -

Epoch 1/10

```
2/2-----149s 124s/step - accuracy: 0.3019 - loss: 2.1415 - val_accuracy: 0.0697
- val_loss: 2.9922
```

Epoch 2/10

```
1/2-----5s 5s/step - accuracy: 1.0000 - loss:
0.8624
```

/usr/local/lib/python3.11/dist-packages/keras/src/trainers/epoch_iterator.py:107:

UserWarning: Your input ran out of data; interrupting training. Make sure that your dataset

or generator can generate at least `steps_per_epoch * epochs` batches. You may need to use the `repeat ()` function when building your dataset.

self._interrupted_warning()

2/2-----85s 80s/step - accuracy: 1.0000 - loss: 0.8624 - val_accuracy: 0.0721 -

val_loss: 3.4239

Epoch 3/10

2/2-----204s 145s/step - accuracy: 1.0000 - loss: 0.3544 - val_accuracy: 0.0697

- val_loss: 4.6668

Epoch 4/10

2/2-----85s 80s/step - accuracy: 1.0000 - loss: 0.0885 - val_accuracy: 0.0721 -

val_loss: 5.2860

Epoch 5/10

2/2-----147s 140s/step - accuracy: 1.0000 - loss: 0.0437 - val_accuracy: 0.0697

- val_loss: 6.4060

Epoch 6/10

2/2-----84s 79s/step - accuracy: 1.0000 - loss: 0.0152 - val_accuracy: 0.0673 -

val_loss: 6.9301

Epoch 7/10

2/2-----123s 87s/step - accuracy: 1.0000 - loss: 0.0069 - val_accuracy: 0.0721 -

val_loss: 7.7398

Epoch 8/10

2/2-----146s 142s/step - accuracy: 1.0000 - loss: 0.0044 - val_accuracy: 0.0673

- val_loss: 8.1362

Epoch 9/10

2/2-----119s 88s/step - accuracy: 1.0000 - loss: 0.0025 - val_accuracy: 0.0673 -

val_loss: 8.7922

Epoch 10/10

2/2-----87s 82s/step - accuracy: 1.0000 - loss: 9.5506e-04 - val_accuracy: 0.0601

- val_loss: 9.1181

<keras.src.callbacks.history.History at 0x7c00eaa14650>

Accuracy is 7 %. The classification report is as follows: -

Classification Report

| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0 | 0.07 | 1.00 | 0.13 | 30 |
| 1 | 0.00 | 0.00 | 0.00 | 44 |
| 2 | 0.00 | 0.00 | 0.00 | 54 |
| 3 | 0.00 | 0.00 | 0.00 | 19 |
| 4 | 0.00 | 0.00 | 0.00 | 42 |
| 5 | 0.00 | 0.00 | 0.00 | 90 |
| 6 | 0.00 | 0.00 | 0.00 | 49 |
| 7 | 0.00 | 0.00 | 0.00 | 30 |
| 8 | 0.00 | 0.00 | 0.00 | 24 |
| 9 | 0.00 | 0.00 | 0.00 | 30 |
| 10 | 0.00 | 0.00 | 0.00 | 21 |
| accuracy | | | 0.07 | 433 |
| macro avg | 0.01 | 0.09 | 0.01 | 433 |
| weighted avg | 0.00 | 0.07 | 0.01 | 433 |

Confusion matrix is as follows: -

Confusion Matrix:

```
[ [30  0  0  0  0  0  0  0  0  0  0  0]
  [44  0  0  0  0  0  0  0  0  0  0  0]
  [54  0  0  0  0  0  0  0  0  0  0  0]
  [19  0  0  0  0  0  0  0  0  0  0  0]
  [42  0  0  0  0  0  0  0  0  0  0  0]
  [90  0  0  0  0  0  0  0  0  0  0  0]
  [49  0  0  0  0  0  0  0  0  0  0  0]
  [30  0  0  0  0  0  0  0  0  0  0  0]
  [24  0  0  0  0  0  0  0  0  0  0  0]
  [30  0  0  0  0  0  0  0  0  0  0  0]
  [21  0  0  0  0  0  0  0  0  0  0  0]]
```

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I. Efficient Net B2.

The available data must be preprocessed and applied to EfficientNet B2. The training of Efficient Net B2 is as follows: -

Epoch 1/10

2/2-----206s 195s/step - accuracy: 0.3333 - loss: 1.6372 - val_accuracy: 0.0673

- val_loss: 7.4695

Epoch 2/10

1/2-----0s 978ms/step - accuracy: 1.0000 - loss: 0.0041

/usr/local/lib/python3.11/dist-packages/keras/src/trainers/epoch_iterator.py:107: UserWarning: Your input ran out of data; interrupting training. Make sure that your dataset or generator can generate at least `steps_per_epoch * epochs` batches. You may need to use the `repeat()` function when building your dataset.

self._interrupted_warning()

2/2-----20s 19s/step - accuracy: 1.0000 - loss: 0.0041 - val_accuracy: 0.0697 -

val_loss: 9.8821

Epoch 3/10

2/2-----20s 19s/step - accuracy: 1.0000 - loss: 2.5049e-04 - val_accuracy: 0.0721

- val_loss: 13.7323

Epoch 4/10

2/2-----21s 20s/step - accuracy: 1.0000 - loss: 7.1860e-06 - val_accuracy: 0.0673

- val_loss: 15.4328

Epoch 5/10

2/2-----17s 15s/step - accuracy: 1.0000 - loss: 7.9349e-07 - val_accuracy: 0.0697

- val_loss: 18.1705

Epoch 6/10

2/2-----21s 20s/step - accuracy: 1.0000 - loss: 2.2707e-08 - val_accuracy: 0.0721

- val_loss: 19.2973

Epoch 7/10

2/2-----20s 15s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy:

0.0673 - val_loss: 21.4803

Epoch 8/10

2/2-----21s 20s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy:

0.0697 - val_loss: 22.3184

Epoch 9/10

2/2-----17s 15s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy:

0.0673 - val_loss: 23.9563

Epoch 10/10

2/2-----20s 19s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy:

0.0697 - val_loss: 24.5746

<keras.src.callbacks.history.History at 0x7f4db18e9210>

The accuracy is 7 %. The classification report is as follows: -

Classification Report

| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0 | 0.07 | 1.00 | 0.13 | 30 |
| 1 | 0.00 | 0.00 | 0.00 | 44 |
| 2 | 0.00 | 0.00 | 0.00 | 54 |
| 3 | 0.00 | 0.00 | 0.00 | 19 |
| 4 | 0.00 | 0.00 | 0.00 | 42 |
| 5 | 0.00 | 0.00 | 0.00 | 90 |
| 6 | 0.00 | 0.00 | 0.00 | 49 |
| 7 | 0.00 | 0.00 | 0.00 | 30 |
| 8 | 0.00 | 0.00 | 0.00 | 24 |
| 9 | 0.00 | 0.00 | 0.00 | 30 |
| 10 | 0.00 | 0.00 | 0.00 | 21 |
| accuracy | | | 0.07 | 433 |
| macro avg | 0.01 | 0.09 | 0.01 | 433 |
| weighted avg | 0.00 | 0.07 | 0.01 | 433 |

Confusion matrix is as follows: -

Confusion Matrix:

```
[[30  0  0  0  0  0  0  0  0  0  0]
 [44  0  0  0  0  0  0  0  0  0  0]
```

```
[ 54 0 0 0 0 0 0 0 0 0 0 0]
[ 19 0 0 0 0 0 0 0 0 0 0 0]
[ 42 0 0 0 0 0 0 0 0 0 0 0]
[ 90 0 0 0 0 0 0 0 0 0 0 0]
[ 49 0 0 0 0 0 0 0 0 0 0 0]
[ 30 0 0 0 0 0 0 0 0 0 0 0]
[ 24 0 0 0 0 0 0 0 0 0 0 0]
[ 30 0 0 0 0 0 0 0 0 0 0 0]
[ 21 0 0 0 0 0 0 0 0 0 0 0]
```

VII. RESULTS

The comparative study of all deep learning models based on accuracy is presented in Table 3 below. The classification reports and confusion matrices of all the models are provided in Tables 4 and 5, respectively.

Table-III: Deep Learning Models Versus Accuracy

| No | Name of Deep Learning Model | Accuracy (%) |
|----|-----------------------------------|--------------|
| 1. | Custom Convolution Neural Network | 7.00 % |
| 2. | Inception V3 | 94 % |
| 3. | VGG16 | 0.0 % |
| 4. | GoogleNet | 14 % |
| 5. | MobileNet | 7 % |
| 6. | ResNet | 7 % |
| 7. | DenseNet | 7 % |
| 8. | Efficient Net B2 | 7 % |

Table-IV: Classification Report Item-Wise Based on Machine Learning Models

| Model | Precision | Recall | f1-score | Support |
|----------------|-----------|--------|----------|---------|
| Custom CNN0 | 0.07 | 1.0 | 0.13 | 30 |
| Custom CNN1 | 0 | 0 | 0 | 44 |
| Custom CNN2 | 0 | 0 | 0 | 54 |
| Custom CNN3 | 0 | 0 | 0 | 19 |
| Custom CNN4 | 0 | 0 | 0 | 42 |
| Custom CNN5 | 0 | 0 | 0 | 90 |
| Custom CNN6 | 0 | 0 | 0 | 49 |
| Custom CNN7 | 0 | 0 | 0 | 30 |
| Custom CNN8 | 0 | 0 | 0 | 24 |
| Custom CNN9 | 0 | 0 | 0 | 30 |
| Custom CNN10 | 0 | 0 | 0 | 21 |
| Inception V3 3 | 1.00 | 0.94 | 0.97 | 17 |
| Inception V3 6 | 0 | 0 | 0 | 0 |
| VGG16 0 | 0 | 0 | 0 | 1311 |
| VGG16 11 | 0 | 0 | 0 | 0 |
| GoogleNet 1 | 1.00 | 0.14 | 0.25 | 85 |
| GoogleNet 5 | 0 | 0 | 0 | 0 |
| GoogleNet 6 | 0 | 0 | 0 | 0 |
| GoogleNet 7 | 0 | 0 | 0 | 0 |
| GoogleNet 9 | 0 | 0 | 0 | 0 |
| GoogleNet 10 | 0 | 0 | 0 | 0 |
| GoogleNet 11 | 0 | 0 | 0 | 0 |
| ResNet 0 | 0.07 | 1.0 | 0.13 | 30 |
| ResNet 1 | 0 | 0 | 0 | 44 |
| ResNet 2 | 0 | 0 | 0 | 54 |
| ResNet 3 | 0 | 0 | 0 | 19 |
| ResNet 4 | 0 | 0 | 0 | 42 |
| ResNet 5 | 0 | 0 | 0 | 90 |
| ResNet 6 | 0 | 0 | 0 | 49 |
| ResNet 7 | 0 | 0 | 0 | 30 |
| ResNet 8 | 0 | 0 | 0 | 24 |
| ResNet 9 | 0 | 0 | 0 | 30 |
| ResNet 10 | 0 | 0 | 0 | 21 |
| DenseNet 0 | 0.07 | 1.0 | 0.13 | 30 |
| DenseNet 1 | 0 | 0 | 0 | 44 |
| DenseNet 2 | 0 | 0 | 0 | 54 |
| DenseNet 3 | 0 | 0 | 0 | 19 |
| DenseNet 4 | 0 | 0 | 0 | 42 |
| DenseNet 5 | 0 | 0 | 0 | 90 |

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| | | | | |
|---------------------|------|-----|------|----|
| DenseNet 6 | 0 | 0 | 0 | 49 |
| DenseNet 7 | 0 | 0 | 0 | 30 |
| DenseNet 8 | 0 | 0 | 0 | 24 |
| DenseNet 9 | 0 | 0 | 0 | 30 |
| DenseNet 10 | 0 | 0 | 0 | 21 |
| Efficient Net B2 0 | 0.07 | 1.0 | 0.13 | 30 |
| Efficient Net B2 1 | 0 | 0 | 0 | 44 |
| Efficient Net B2 2 | 0 | 0 | 0 | 54 |
| Efficient Net B2 3 | 0 | 0 | 0 | 19 |
| Efficient Net B2 4 | 0 | 0 | 0 | 42 |
| Efficient Net B2 5 | 0 | 0 | 0 | 90 |
| Efficient Net B2 6 | 0 | 0 | 0 | 49 |
| Efficient Net B2 7 | 0 | 0 | 0 | 30 |
| Efficient Net B2 8 | 0 | 0 | 0 | 24 |
| Efficient Net B2 9 | 0 | 0 | 0 | 30 |
| Efficient Net B2 10 | 0 | 0 | 0 | 21 |

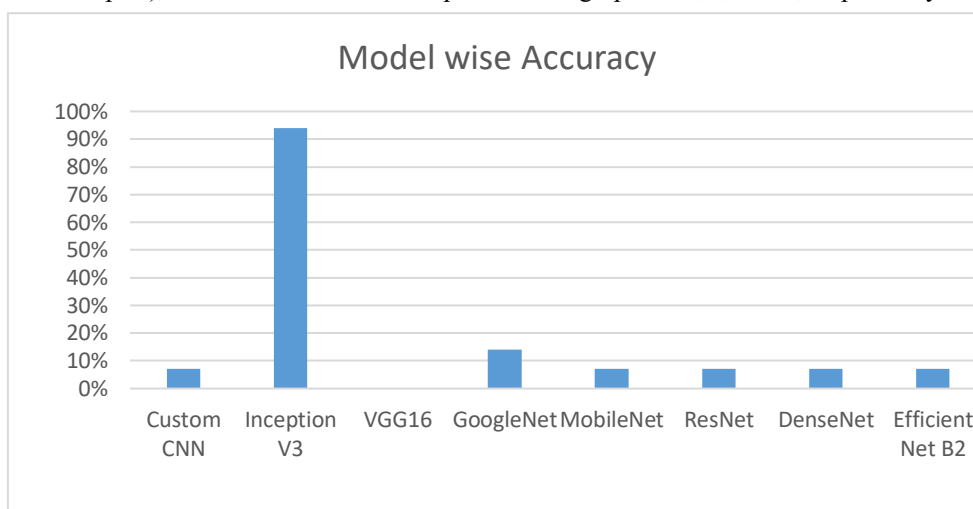
Table-V: Confusion Matrix based on Deep Learning Models

| Model | True Positive | False Positive | False Negative | True Negative |
|--------------------|---------------|----------------|----------------|---------------|
| Custom CNN0 | 30 | 403 | 0 | 0 |
| Custom CNN1 | 44 | 389 | 0 | 0 |
| Custom CNN2 | 54 | 379 | 0 | 0 |
| Custom CNN3 | 19 | 414 | 0 | 0 |
| Custom CNN4 | 42 | 391 | 0 | 0 |
| Custom CNN5 | 90 | 343 | 0 | 0 |
| Custom CNN6 | 49 | 384 | 0 | 0 |
| Custom CNN7 | 30 | 403 | 0 | 0 |
| Custom CNN8 | 24 | 409 | 0 | 0 |
| Custom CNN9 | 0 | 403 | 0 | 0 |
| Custom CNN10 | 21 | 412 | 0 | 0 |
| Inception V3 3 | 17 | 416 | 0 | 0 |
| Inception V3 6 | 0 | 0 | 0 | 0 |
| VGG16 0 | 1311 | 0 | 0 | 0 |
| VGG16 11 | 0 | 0 | 0 | 0 |
| GoogleNet 1 | 12 | 19 | 0 | 0 |
| GoogleNet 5 | 0 | 0 | 0 | 0 |
| GoogleNet 6 | 0 | 0 | 0 | 0 |
| GoogleNet 7 | 0 | 0 | 0 | 0 |
| GoogleNet 9 | 0 | 0 | 0 | 0 |
| GoogleNet 10 | 0 | 0 | 0 | 0 |
| GoogleNet 11 | 0 | 0 | 0 | 0 |
| ResNet 0 | 30 | 403 | 0 | 0 |
| ResNet 1 | 44 | 389 | 0 | 0 |
| ResNet 2 | 54 | 379 | 0 | 0 |
| ResNet 3 | 19 | 414 | 0 | 0 |
| ResNet 4 | 42 | 391 | 0 | 0 |
| ResNet 5 | 90 | 343 | 0 | 0 |
| ResNet 6 | 49 | 384 | 0 | 0 |
| ResNet 7 | 30 | 403 | 0 | 0 |
| ResNet 8 | 24 | 409 | 0 | 0 |
| ResNet 9 | 30 | 403 | 0 | 0 |
| ResNet 10 | 21 | 412 | 0 | 0 |
| DenseNet 0 | 30 | 403 | 0 | 0 |
| DenseNet 1 | 44 | 389 | 0 | 0 |
| DenseNet 2 | 54 | 379 | 0 | 0 |
| DenseNet 3 | 19 | 414 | 0 | 0 |
| DenseNet 4 | 42 | 391 | 0 | 0 |
| DenseNet 5 | 90 | 343 | 0 | 0 |
| DenseNet 6 | 49 | 384 | 0 | 0 |
| DenseNet 7 | 30 | 403 | 0 | 0 |
| DenseNet 8 | 24 | 409 | 0 | 0 |
| DenseNet 9 | 30 | 403 | 0 | 0 |
| DenseNet 10 | 21 | 412 | 0 | 0 |
| Efficient Net B2 0 | 30 | 403 | 0 | 0 |
| Efficient Net B2 1 | 44 | 389 | 0 | 0 |
| Efficient Net B2 2 | 54 | 379 | 0 | 0 |
| Efficient Net B2 3 | 19 | 414 | 0 | 0 |
| Efficient Net B2 4 | 42 | 391 | 0 | 0 |
| Efficient Net B2 5 | 90 | 343 | 0 | 0 |
| Efficient Net B2 6 | 49 | 384 | 0 | 0 |

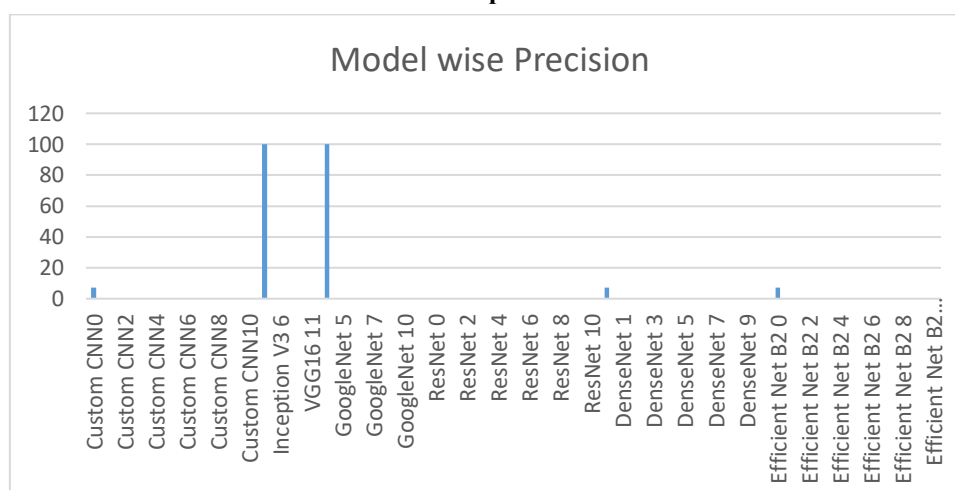


| | | | | |
|---------------------|----|-----|---|---|
| Efficient Net B2 7 | 30 | 403 | 0 | 0 |
| Efficient Net B2 8 | 24 | 409 | 0 | 0 |
| Efficient Net B2 9 | 30 | 403 | 0 | 0 |
| Efficient Net B2 10 | 21 | 412 | 0 | 0 |

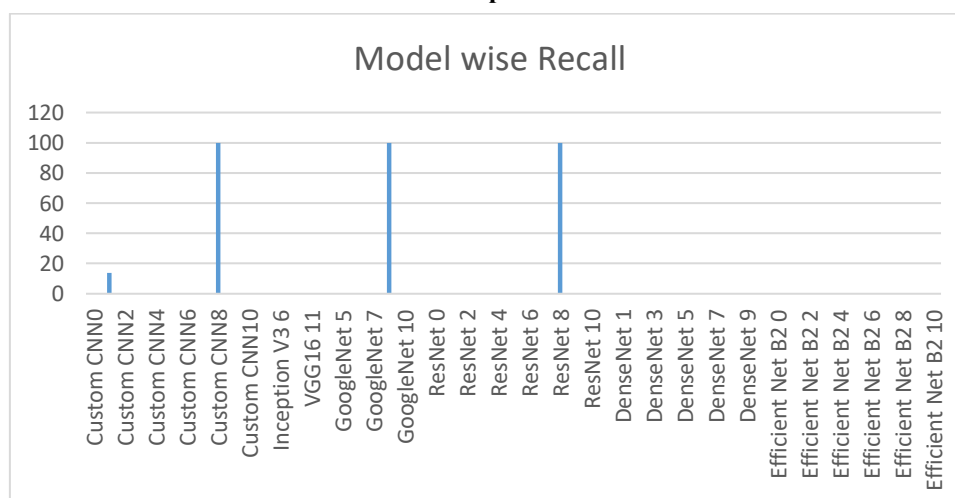
The Change in values of accuracy has been furnished in a graph named Graph 1. The changes in values of precision, recall, F1-score (classification report), and confusion matrix are presented in graphs 2, 3, 4, and 5, respectively.



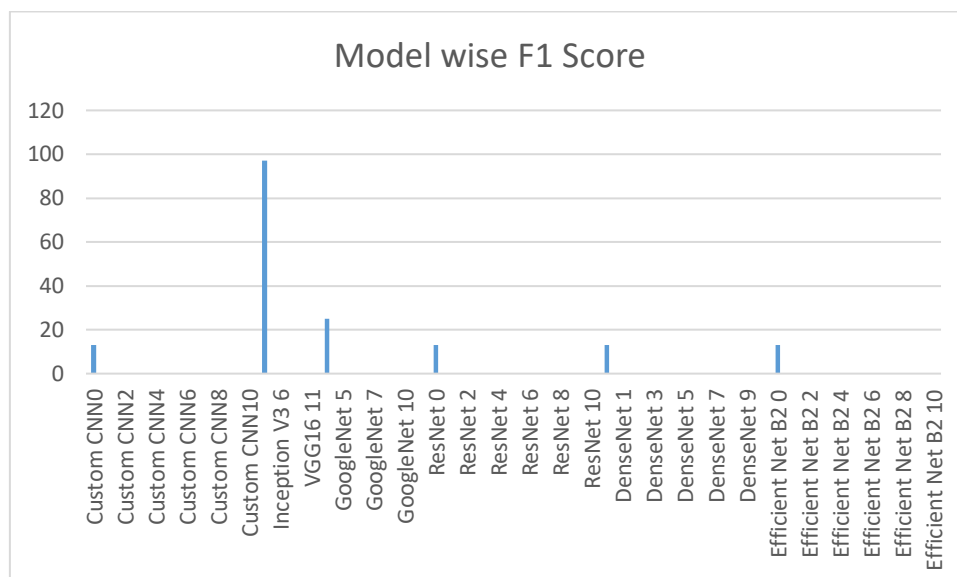
Graph 1



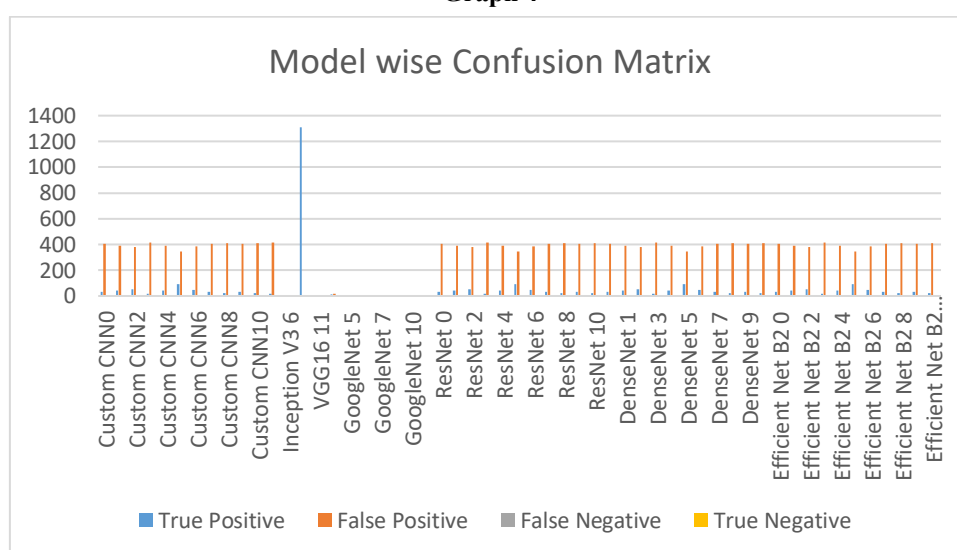
Graph 2



Graph 3



Graph 4



Graph 5

VIII. CONCLUSIONS

Based on the observations from Table 3, Inception V3 demonstrates superior performance as compared to the other models. Its strength lies in delivering high accuracy and efficiency in classification tasks. Renowned for its strong capabilities in classification, prediction, and object detection, Inception V3 often surpasses architectures like ResNet-50. Its key advantages include enhanced accuracy, computational efficiency, and a strong ability to detect complex patterns.

Inception v3 is a powerful and versatile image recognition model renowned for its high accuracy and ability to handle a wide range of input image sizes without requiring extensive pre-processing. It has achieved great success in tasks such as image classification and object detection, often outperforming other architectures in terms of performance metrics, including accuracy and F1-score.

In contrast, ResNet models present certain limitations, such as high computational demands during training and inference, susceptibility to overfitting, and the need for extensive customisation to achieve optimal results for specific tasks. Similarly, DenseNet-121, a variant of the DenseNet family, faces drawbacks like increased memory usage, computational

intensity, and a tendency to overfit. EfficientNet-B2, while designed with efficiency in mind, may fall short in scenarios requiring extremely high accuracy or the processing of highly complex datasets, due to its balance between model size and performance. MobileNet models may also experience reduced accuracy, particularly after post-training quantisation, and may underperform on larger-scale or highly specialised tasks.

In summary, Inception V3 stands out as a top-performing model among those evaluated, offering a strong balance of accuracy, efficiency, and robustness.

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After aggregating input from all authors, I must verify the accuracy of the following information as the article's author.

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- **Funding Support:** This article has not been funded by any organizations or agencies. This independence ensures that the research is



conducted with objectivity and without any external influence.

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- **Data Access Statement and Material Availability:** The adequate resources of this article are publicly accessible.
- **Authors Contributions:** Each author has individually contributed to the article. Madhab Paul Choudhury: Often, the researcher who has done the most substantial work on the project is. Typically writes the first draft of the manuscript. May lead the conceptual design and data acquisition. Ensures the accuracy and integrity of the research. Maybe the corresponding author, but not always. Dr. Jagannibas Paul Choudhury: Handles all communication with the journal during the submission, review, and publication process. Responsible for ensuring all authors have approved the final version of the manuscript. May be responsible for addressing questions and concerns from the journal or reviewers.

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AUTHOR'S PROFILE



Madhab Paul Choudhury (MPC), Shree Madhab Paul Choudhury has acquired a B.Tech. in Computer Science & Engineering from Kalyani Government Engineering College, Kalyani, under Maulana Abul Kalam Azad University of Technology in 2016, and an M.Tech. in Computer Science & Engineering from the National Institute of Technology, Jamshedpur, in 2023. He has served 3 years and 6(six) months (approx) in Tata Consultancy Services as a Systems Engineer. Now he is pursuing a PhD (Engg.) from IIT ISM Dhanbad. The primary area of research focuses on healthcare applications utilising Machine Learning and Deep Learning models. Earlier, he worked in the field of Soft Computing. Shree Madhab Paul Choudhury has published seven articles in reputed journals and conference proceedings.



Dr. Jagannibas Paul Choudhury has passed the B.E.Tel.E. (Hons.) in Electronics & Tele Communication Engineering from Jadavpur University in 1979 and completed an M.Tech. in Control & Automation Engineering from IIT Kharagpur in 1982. He has done a PhD (Engg.) from Jadavpur University in 2002. He has over 20 years of experience in Teaching, Research, and Administration. Earlier, he had an experience of 12 years(approx) in Kalyani Government Engineering College, Kalyani, West Bengal. He has experience of approximately. 6(six) years as Professor (IT) there. Now he is Professor (Computer Science & Engineering) at Narula Institute of Technology, Kolkata. He has published over 100 research papers in reputable journals and conference proceedings.

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