

Diabetes Diagnosis Using Pre-Trained Deep Learning Model

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Abstract: Since prevention is always preferable to treatment, disease prediction is essential for efficient prevention and management. One of the most serious diseases in the world is diabetes. Significant predictive potential of diabetes is shown by BMI, waist circumference, serum urate levels, GGT, waist-hip ratio, HDL cholesterol, family history of diabetes, and plasma glucose. Human stress can impact blood glucose regulation, metabolic activity, and insulin resistance, all of which can have an impact on diabetic levels. This article discusses how to anticipate the disease using pre-trained deep learning models. ResNet is among them. It is an image classification model that is specifically designed to analyze retinal images and find indications of diabetic retinopathy, a diabetes condition that can cause visual problems. To improve the quality of training images, methods like augmentation, normalization, and scaling are applied. A classification or regression score showing the degree of severity is the model's output. Its deeply layered structure facilitates the efficient learning of intricate diabetic retinopathy patterns. The program predicts if a patient has diabetes and lowers the chance of visual loss through early detection based on the patient's current medical record.

Keywords: diabetic retinopathy, deep layered structure, deep learning, ResNet, diabetic symptoms, diabetes prediction, and pre-trained model.

INTRODUCTION:

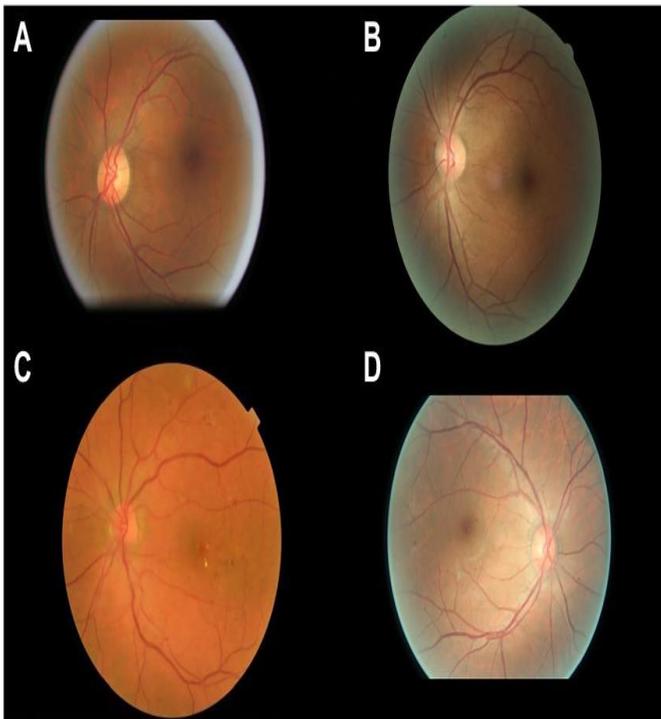
Millions of individuals worldwide suffer with

diabetes mellitus, a chronic metabolic disease that, if unchecked, can have serious consequences. Diabetic retinopathy (DR) is one of the main causes of blindness among its numerous side effects. Effective management and treatment of diabetes and its related problems, including DR, depend on early detection. Clinical tests such as hemoglobin A1c (HbA1c), fasting blood sugar (FBS), and ophthalmologists' manual review of retinal pictures are the foundation of traditional diagnostic techniques. Nevertheless, these techniques are labor-intensive, time-consuming, and prone to human error. Automated diagnostic tools have demonstrated great promise in raising the precision and effectiveness of diabetes detection with developments in deep learning and artificial intelligence (AI). Convolutional neural networks, or CNNs, have become extremely effective tools for medical image processing, providing cutting-edge results in tasks like segmentation and classification. The ability of ResNet (Residual Network) to solve the vanishing gradient issue and allow deeper networks to effectively learn complicated features has made it one of the most successful CNN architectures. This study introduces ResNet, a deep learning-based method for identifying diabetic retinopathy and diagnosing diabetes. To arrive at a reliable diagnosis, the model makes use of clinical data and medical imaging (fundus pictures). The residual connections in ResNet enable better feature extraction, which raises the detection accuracy of diabetes and associated consequences. By offering a dependable, automated diagnostic tool,

the proposed system seeks to support medical practitioners and eventually improve patient outcomes and early intervention. provide an intuitive interface for determining if a patient has diabetic retinopathy. The fundus image must be

uploaded by the user; it then goes through preprocessing, and the trained model makes predictions about the outcome.

Neural networks with additional layers performed significantly better when the ResNet architecture was used. The model for classifying fundus images into five categories—No_DR, Mild, Moderate, Proliferate, and Severe—is trained using the ResNet architecture.



LITERATURE SURVEY:

1. Diabetic Retinopathy Detection Using Deep Learning

This study investigates the detection of diabetic retinopathy from retinal pictures using convolutional neural networks (CNNs). For efficient feature extraction and classification, it emphasizes the advantages of transfer learning using pre-trained models such as ResNet and VGG. The article is titled "Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs." JAMA (2016)

2. Machine Learning-Based Diabetes Predictive Models

Based on clinical characteristics including age, BMI, and family history, the study examines many machine

learning models (such as SVM, Random Forest, and Logistic Regression) for predicting the onset of diabetes. Citation: "A Comparative Analysis of Machine Learning Algorithms for Diabetes Prediction." Journal of Biomedical Informatics, 2019. Alva, A., et al.

3. Classification of Diabetic Retinopathy Using ResNet-50

This study uses a collection of retinal pictures to show how well the ResNet-50 architecture classifies diabetic retinopathy. The study illustrates the better feature learning capabilities of deep residual networks by comparing performance with conventional models. The study "Diabetic Retinopathy Detection Using ResNet-50 with Transfer Learning" by Wang, X., et al. is cited. IEEE Access, 2018.

4. Predicting Diabetes Through Ensemble Methods

In order to forecast diabetes, the study assesses ensemble learning methods including Random Forest and Gradient Boosting. It demonstrates how integrating several models can increase the precision of predictions. Shukla, A., et al. "A Novel Ensemble Learning Approach for Diabetes Prediction." Expert Systems with Applications, 2020, is cited.

5. CNN-Based Automatic Diagnosis of Diabetic Retinopathy

The automated diagnosis of diabetic retinopathy using deep CNNs is the main emphasis of this work. In order to improve model performance, the study addresses preprocessing methods such as picture augmentation and normalization.

"Deep Convolutional Neural Networks for Diabetic Retinopathy Detection." Computers in Biology and Medicine, 2017. Li, Y., et al.

6. Applying Data Mining Methods to Predict Diabetes

With an emphasis on clinical datasets and patient medical records, this study investigates the use of data mining techniques (such as decision trees and k-nearest neighbors) for diabetes prediction. "A Data Mining Approach to Predicting Diabetes Mellitus." Journal of Computer Science and Technology, 2018. Pickle, A., et al.

7. A Deep Learning Structure for Diagnosing Diabetic Retinopathy

The study offers a deep learning architecture for diabetic retinopathy classification that incorporates CNNs and picture augmentation methods.

The study highlights the significance of training models on extensive medical data and the quality of datasets. See Sun et al.'s article in the Journal of Healthcare Engineering from 2020, "Deep Learning-Based Diabetic Retinopathy Detection System."

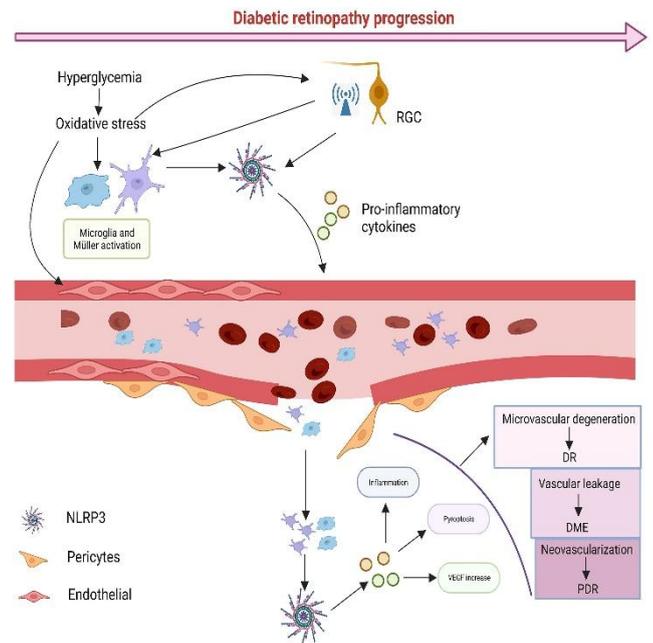
8. Applying Machine Learning Models to Predict Type-2 Diabetes

This study demonstrates how several machine learning methods, such as logistic regression and neural networks, can be used to forecast an individual's risk of developing type 2 diabetes based on genetic and lifestyle characteristics.

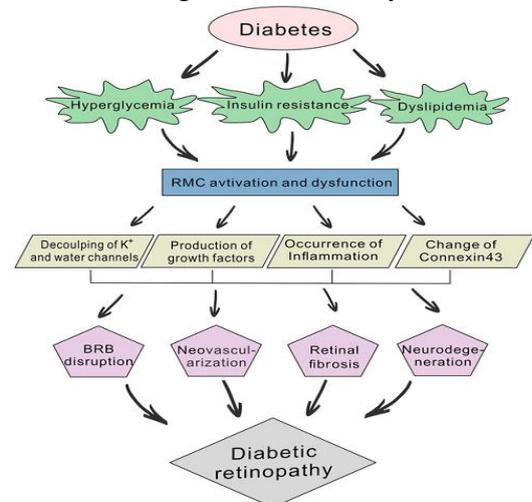
Source: IEEE Transactions on Biomedical Engineering, 2019; Joshi, A., et al., "Machine Learning Models for Predicting Type 2 Diabetes Risk."

[1] examined two fundus images from each eye that were examined by a retinal specialist. Two algorithms were independently applied on the dataset by the author. The Eye Check method produced an AUC of 0.839, whereas the Challenge 2009 algorithm produced an AUC of 0.821. Gargey et al. [2] created a tool for automatically identifying diabetic retinopathy and categorized the photos as either healthy or DR-afflicted.

The model was evaluated externally by the author using the public MESSIDOR 2 and E-Ophtha databases, yielding AUC values of 0.94 and 0.95, respectively. Edward Rajan and Wilfred Franklin [3] suggested an automated method for detecting blood vessels with a high degree of accuracy. The accuracy of the author's automated segmentation algorithm, which was applied to DRIVE database photos, was 95.03%. Image-level, lesion-specific, and anatomical components were used by Antal and Hajdu et al. [4]. The author developed classifiers and tested them on the publicly accessible Messidor dataset, yielding an AUC of 0.989. Liskowski et al. [5] employed deep neural networks and a supervised technique on image datasets. also suggested a supervised approach that uses deep neural networks on unprocessed image data. On preprocessed photos, however, they can operate more effectively.



The results of the author structured prediction and classification process have an accuracy of 0.97 and an AUC of more than 0.99. In fine vessels, the results likewise showed sensitivity greater than 0.87. Revathy et al [6], divided the data into three classes: mild, moderate non-proliferative diabetic retinopathy, and proliferative diabetic retinopathy. This was done using an SVM-based training approach. Using a variety of classification techniques, the approach demonstrated good accuracy of 82%.



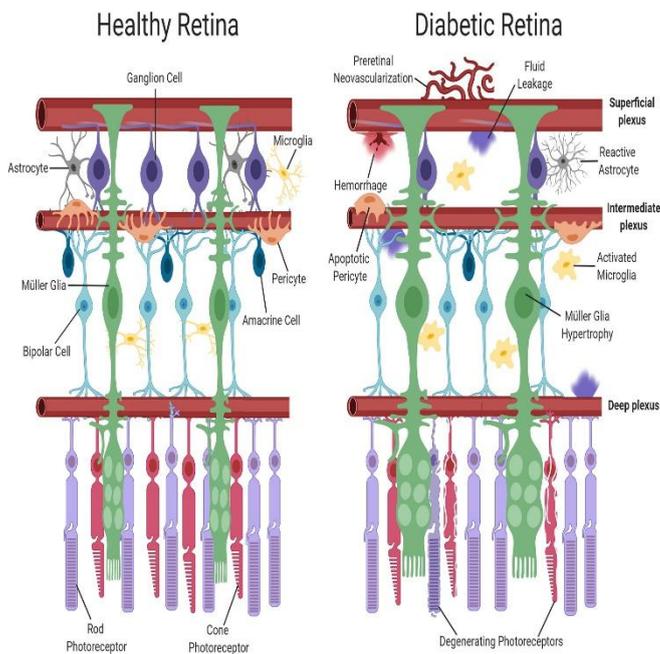
BACKGROUND STUDY:

The chronic metabolic disease known as diabetes mellitus is brought on by the body's incapacity to make or use insulin efficiently, which raises blood sugar levels. Uncontrolled diabetes can lead to serious consequences over time that impact the heart, kidneys, nerves, eyes, and other organs. Diabetic retinopathy (DR), a disorder that affects the retinal blood vessels and causes vision impairment and, in extreme cases, blindness, is one of the most prevalent and dangerous side effects of diabetes.

Based on the extent of retinal damage, diabetic retinopathy is a progressive condition that is divided into several phases. **The following are the five main stages of DR:**

1. No Diabetic Retinopathy (No DR): There are no obvious symptoms of damage to the retina, which is good health.

2. Mild Non-Proliferative Diabetic Retinopathy (Mild DR): Microaneurysms, which are tiny enlargements in the retinal blood vessels, may seep fluid into the retina.



3. Moderate Non-Proliferative Diabetic Retinopathy (Moderate DR): This condition involves blockages in the blood vessels that supply the retina, which can result in exudates and hemorrhages and impair vision.

4. Severe Non-Proliferative Diabetic Retinopathy (Severe DR): The retina experiences oxygen shortage due to more blocked blood vessels, which causes aberrant blood vessel growth.

5. Proliferative Diabetic Retinopathy (PDR): The most severe stage, in which the retina develops new, delicate blood vessels. These vessels have the potential to burst and bleed profusely, which could result in scarring and possibly retinal detachment and total blindness.

Challenges in Traditional Diabetic Retinopathy Diagnosis
The traditional method of diagnosing DR involves fundus photography, where high-resolution images of the retina are captured and manually examined by ophthalmologists. This process requires expert knowledge, specialized equipment, and significant time, making large-scale screening difficult, especially in rural and underserved areas. Moreover, human diagnosis is subject to inter-observer variability, meaning different specialists may interpret the same image differently, leading to inconsistencies.

To address these challenges, artificial intelligence (AI) and deep learning (DL) models have been developed to automate and enhance the accuracy of DR diagnosis. Deep learning-based image classification can process thousands of retinal images in seconds, providing quick and accurate diagnostic results. This technology helps in early detection, enabling timely treatment and reducing the risk of blindness.

Researchers used handmade feature extraction in traditional machine learning algorithms for DR detection, manually identifying features including hemorrhages, microaneurysms, and anomalies in blood vessels. Nevertheless, the scalability and feature generalization of these approaches were constrained. Convolutional Neural Networks (CNNs), a type of deep learning, have made it possible for AI models to automatically extract intricate information from retinal images without the need for human interaction.

METHODOLOGY:

The project implements a deep learning-based automated diabetic retinopathy (DR) detection system employing a combination of hardware and software resources. A GPU (like the NVIDIA RTX 3080 or Tesla V100) is recommended for faster model training on the hardware side, in addition to a high-performance CPU (like the AMD Ryzen 7/9 or Intel Core i7/i9), at least 16GB of RAM, and 100GB of SSD storage for effective handling of big diabetes.

The Python programming language (version 3.7 or later) and deep learning frameworks like PyTorch are part of the software stack. A number of auxiliary libraries are utilized, such as NumPy for numerical operations, PIL (Pillow) for image preprocessing, Pandas for handling CSV files, Sklearn for dataset splitting, and Torchvision for working with pretrained models.

Data preparation is the initial stage of the procedure, during which retinal images are loaded and given severity labels using a CSV file that goes with them. The `train_test_split()` function divides the dataset into 80% training and 20% validation sets to guarantee balanced training. The photos are transformed into tensors, resized to 224×224 pixels, then normalized with mean and standard deviation values that match ImageNet's training parameters before being fed into the deep learning model.

1. Diabetes Prediction Information

Predicting diabetes early on is crucial for avoiding complications and guaranteeing prompt medical attention. The Pima Indians Diabetes Dataset, which is accessible on websites like Kaggle and the UCI Machine Learning Repository, is among the most widely used datasets for diabetes prediction. The medical records of female Pima Indian women aged 21 and up who have a history of having a greater prevalence of diabetes make up this dataset. Numerous clinical and biological characteristics in the sample are significant predictors of diabetes. Blood pressure, insulin levels, age, body mass index (BMI), skin thickness, and glucose levels are a few of the important characteristics. These variables offer important information about a person's risk of diabetes and metabolic health. Furthermore, other significant characteristics that aid in the a concept

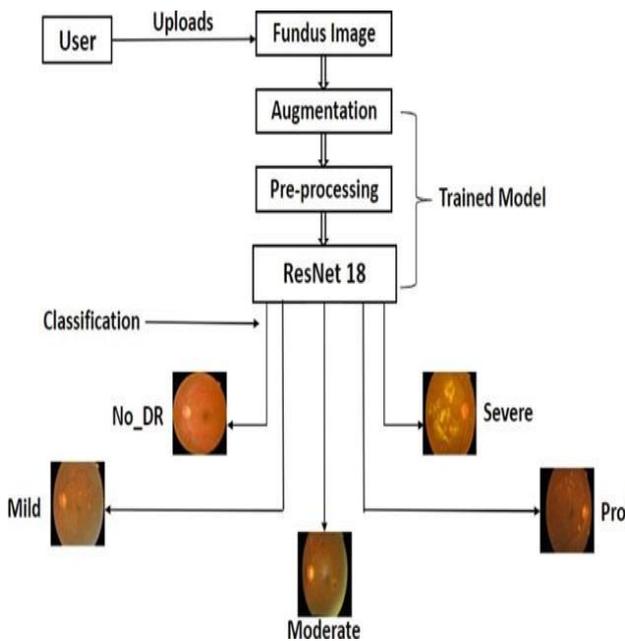
determining a person's risk of acquiring diabetes include the number of pregnancies and diabetes pedigree function, a score that gauges a person's genetic sensitivity to the condition.

2. Image Dataset of Diabetic Retinopathy

Diabetic retinopathy (DR) detection attempts to evaluate visual issues brought on by persistently elevated blood sugar levels, whereas diabetes prediction concentrates on identifying those who are at risk of acquiring diabetes. Early identification of diabetic retinopathy is essential because it is a leading cause of vision loss and blindness globally. To create models for deep learning These algorithms identify patterns in retinal pictures, such as anomalies in blood vessels, hemorrhages, and Classification accuracy is further increased by the use of transfer learning, in which models that have been pretrained on sizable datasets, such as ImageNet, are refined on medical pictures. The APTOS 2019 Blindness Detection Dataset, which is accessible on Kaggle, is one such dataset. The high-resolution retinal fundus images in this dataset are categorized by the degree of diabetic retinopathy. Convolutional neural networks (CNNs), which are based on deep learning, have been widely employed to analyze and categorize these retinal images into various severity levels. When it comes to automating DR diagnosis, pretrained models like ResNet, VGG16, EfficientNet, and InceptionNet have shown excellent accuracy.

3. Medical Records of Patients

Diagnostic accuracy can be greatly increased by including real-world patient medical records in addition to diabetes prediction databases and retinal image datasets. Real-world data offers a more thorough understanding of a patient's medical history, lifestyle, and genetic factors, even while organized databases like the Pima Indians Diabetes Dataset include helpful biometric and clinical aspects. Information such as food patterns, stress levels, cholesterol levels, physical activity levels, family history of diabetes, and current blood test results can all be found in a patient's medical file. Hospital partnerships, wearable health tracking devices, or APIs from medical databases can all be used to gather this kind of data. For instance, wearable technology such as glucose monitors and smartwatches can offer real-time information on heart rate, activity levels, and blood sugar variations, which can be utilized to enhance prediction models.



RESULT AND ANALSYS:

The goal of this project is to create a system that can:

- Identify people at risk of diabetes accurately, The system can forecast a person's chance of acquiring diabetes by examining a number of variables, including age, family history, lifestyle choices, and genetic predispositions. This makes it possible to avoid or postpone the disease's start with early intervention and lifestyle changes.
- Assess the degree of diabetic retinopathy: This dangerous eye condition that can result in blindness is caused by diabetes. Retinal pictures may be reliably classified by the system to determine the severity of diabetic retinopathy, enabling prompt and suitable therapy actions.
- Facilitate early identification and prevention: The method enables prompt interventions and preventative measures by identifying those who are at high risk of developing diabetes and diagnosing diabetic retinopathy in its early stages. This can greatly lower the chance of developing major side effects from diabetes, such as nerve damage, heart disease, renal disease, and eyesight loss.

Effective diabetes control requires early detection and intervention. By enhancing the early detection and treatment of diabetes and its related complications, this project has the

potential to have a substantial positive influence on public health and, eventually, improve the health of those who have the disease.

PERFORMANCE MATRIX:

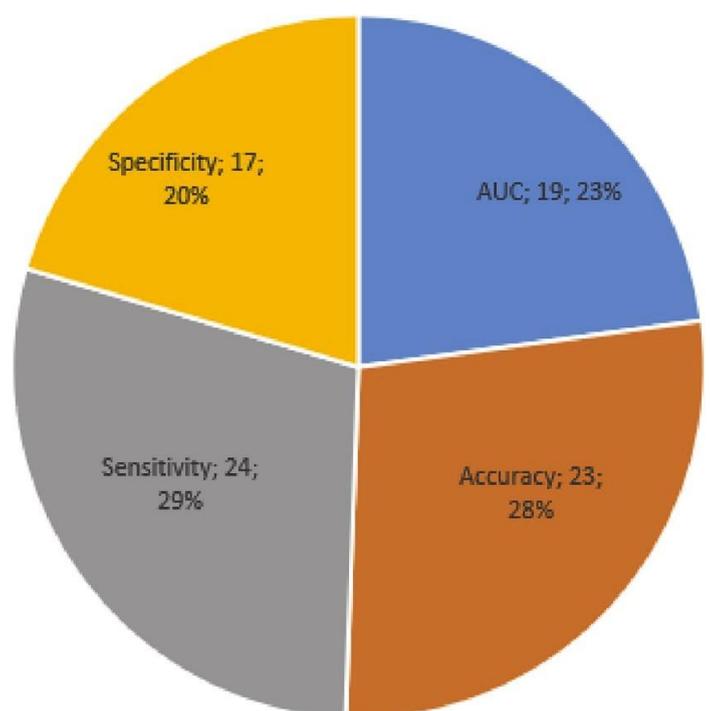
To assess the classification performance of DL algorithms, a variety of performance metrics are used. Area under the ROC curve (AUC), sensitivity, specificity, and accuracy are the metrics most frequently employed in DL. The percentage of aberrant images classified as abnormal is known as sensitivity, and the percentage of normal images categorized as normal is known as specificity [65]. Plotting sensitivity against specificity yields the AUC graph. The proportion of correctly categorized photos is known as accuracy. The equations for each measurement are as follows.

$$\text{Specificity} = \text{TN} / (\text{TN} + \text{FP}) \tag{1}$$

$$\text{Sensitivity} = \text{TP} / (\text{TP} + \text{FN}) \tag{2}$$

$$\text{Accuracy} = (\text{TN} + \text{TP}) / (\text{TN} + \text{TP} + \text{FN} + \text{FP}) \tag{3}$$

The number of disease-classified photos is known as the true positive (TP). False positives (FP) are the number of normal images classified as disease, whereas true negatives (TN) are the number of normal images categorized as normal. The quantity of illness images that are categorized as normal is known as a false negative (FN). Figure 5 displays the proportion of performance metrics employed in the studies that are relevant to the current work.



CONCLUSION AND FUTURE SCOPE:

The time needed to make diagnoses is greatly decreased by automated screening devices, which saves ophthalmologists money and labor while ensuring that patients receive treatment on time. Early DR detection is made possible in large part by automated DR detection systems. The types of lesions that develop on the retina determine the phases of DR. The most recent automated methods for detecting and classifying diabetic retinopathy that made use of deep learning techniques were examined in this article. We have presented the publicly accessible common fundus DR datasets and provided a quick overview of deep-learning algorithms. Because of its effectiveness, the majority of researchers have employed CNN for DR image categorization and detection.

Images sent to physicians for scaling in a manual setting are not accurately graded or classified. The ResNet architecture-trained model provides quick diagnosis and prompt response. Using the ResNet architecture, we were able to classify the fundus images with an accuracy of 82%.

ACKNOWLEDGEMENT:

We would like to express our sincere gratitude to everyone who made this initiative possible.

Above all, we want to sincerely thank S. Navya, our mentor, for her invaluable counsel, insightful suggestions, and steadfast support during the research and development stage. Their expertise and assistance have had a significant impact on this endeavor.

We also thank our organization, Raghu Institute of Technology, and project coordinator Dr. S. Vidya Sagar for providing us with the necessary resources, infrastructure, and technical support.

In conclusion, a special gratitude goes out to the open-source community for making this research possible.

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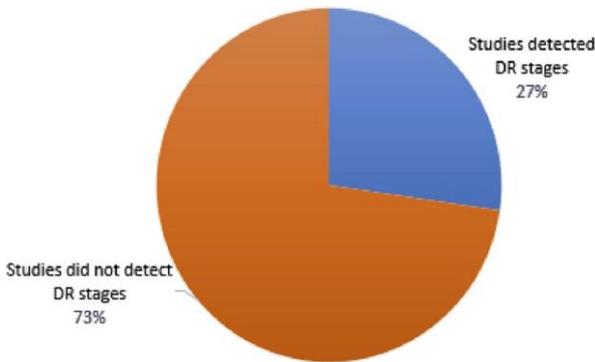


Fig : The percentage of studies that detected DR stages.

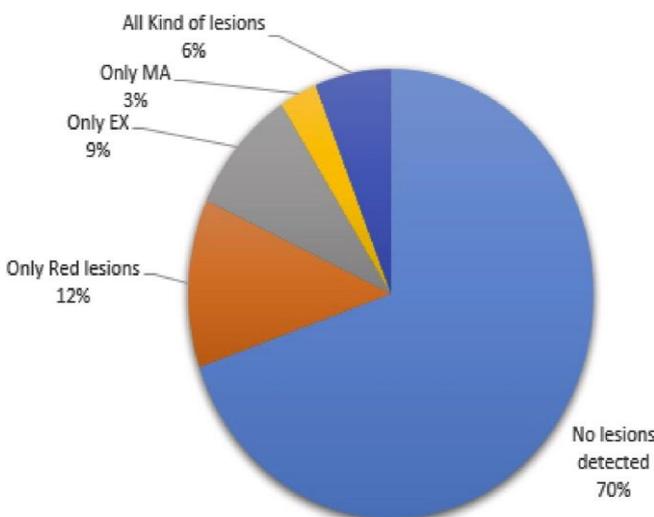


Fig: The percentage of studies that detected DR lesions.

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