AMD DETECTION USING DEEP LEARNING AND NEURAL NETWORKS

PROJECT REPORT

Submitted by

Naveenkumar D(714022201063)

Naveen Kumar J(714022201064)

Sampreetha S(714022201086)

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BONAFIDE CERTIFICATE

Certified that this report titled "AMD detection using deep learning and neural networks" is the bonafide work of **"Naveenkumar D (714022201063), Naveen Kumar J (714022201064), Sampreetha S (714022201086)"**, who carried out the project work under our supervision.

Project Guide

Mr.Varun Kumar.B

Assistant Professor,

Dept. of Information Technology

Co-Ordinator

Dr. R. P. S. Manikandan

Associate Professor,

Dept. of Information Technology

Head of the Department

Mr.Dhinaharan.S

Professor

Dept. of Artificial Intelligence and Data Science

Submitted for the project work viva voce Examination held on……..…..

Internal Examiner **External Examiner**

ABSTRACT

Age-Related Macular Degeneration (AMD) is a leading cause of vision loss among the elderly population, making its early detection crucial for effective intervention. This abstract presents a novel approach for AMD detection utilizing deep learning techniques and neural networks .The proposed system leverages a comprehensive dataset of retinal images, including both fund us photographs and optical coherence tomography (OCT) scans, to train a convolutional neural network (CNN) architecture. The CNN is designed to automatically extract relevant features and patterns from retinal images, facilitating the classification of AMDinto various stages, such as early, intermediate, and advanced.

Key components of our approach include data preprocessing techniques to enhance image quality, data augmentation to mitigate overfitting, and the use of transfer learning from pre-trained models to boost performance. We evaluate the model's accuracy, sensitivity, and specificity on a separate validation dataset, demonstrating its ability to discriminate between AMD and healthy retinas.

Our results show promising performance in AMD detection, suggesting that deep learning-based neural networks have the potential to become valuable tools in the early diagnosis and monitoring of AMD. This research contributes to the ongoing efforts to improve the accessibility and efficiency of AMD screening, ultimately enhancing the quality of life for individuals at risk of this debilitating eye condition.

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Naveenkumar D

Naveen kumar J

Sampreetha S

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CHAPTER 1

INTRODUCTION

In recent years, the field of deep learning and neural networks has experienced remarkable advancements, revolutionizing various domains, including medical diagnostics. One such critical application is the early detection of Age-related Macular Degeneration (AMD), a leading cause of irreversible vision loss among the elderly population. The integration of deep learning techniques into AMD detection holds the promise of enhancing the accuracy, efficiency, and accessibility of diagnostic procedures.

AMD poses a significant public health challenge, and its timely identification is crucial for effective management and intervention. Traditional methods of AMD diagnosis often rely on labor-intensive and subjective manual assessments, making them prone to variability and errors. The emergence of deep learning and neural networks offers an innovative solution by leveraging the power of data-driven algorithms to analyze intricate patterns and features within retinal images.

This enables the detection of subtle changes, anomalies, and early signs of AMD that might escape human observation. By training these networks on large datasets containing diverse examples of healthy and diseased retinas, the models can generalize their knowledge to new, unseen cases.

In this pursuit, the amalgamation of convolutional neural networks (CNNs) and other deep learning architectures holds particular promise. CNNs excel in image analysis tasks due to their inherent ability to capture local patterns through convolutional layers and learn global relationships through pooling and fully connected layers. This enables them to discern intricate features, such as drusen deposits and retinal pigment epithelium abnormalities, indicative of different AMD stages.

The potential impact of AMD detection using deep learning is manifold. Firstly, it can significantly expedite the diagnostic process, providing quicker results and facilitating timely intervention. Secondly, the automation of diagnosis reduces the dependency on scarce ophthalmology expertise, potentially widening access to quality healthcare in underserved areas. Furthermore, as these models continue to learn and improve with more data, their diagnostic accuracy can surpass traditional methods, enhancing the overall quality of patient care.

However, challenges persist, including the need for large, diverse, and well-annotated datasets, as well as robustness against potential biases present in the training data. The interpretability of deep learning models in the medical context also remains a critical concern, as the ability to explain the model's decisions is paramount for gaining clinicians' trust and wider adoption.

In conclusion, the integration of deep learning and neural networks into AMD detection represents a significant step towards more accurate, efficient, and accessible diagnosis. Through the automated analysis of retinal images, these technologies hold the potential to revolutionize how we approach AMD and other medical conditions, ultimately contributing to better patient outcomes and quality of life.

CHAPTER 2

LITERATURE REVIEW

Introduction

In the realm of medical diagnostics, the integration of cutting-edge technologies has brought forth transformative advancements. This project introduces an innovative deep learning framework, powered by convolutional neural networks (CNNs), aimed at revolutionizing the diagnosis of eye conditions based on Optical Coherence Tomography (OCT) images. Focusing on Age-related Macular Degeneration (AMD), a leading cause of vision impairment, the framework seeks to achieve unprecedented levels of accuracy, sensitivity, and specificity by harnessing intricate patterns within retinal scans. By automating the diagnostic process, this framework has the potential to enhance early detection rates, reduce reliance on expert opinions, and ultimately elevate patient outcomes in the field of ophthalmic healthcare.

Existing Solution:

In the field of medical imaging, particularly for retinal diseases like AMD, traditional diagnostic methods often rely on manual assessments by ophthalmologists. These methods can be time-consuming, subjective, and prone to inter-observer variability. Automated solutions using deep learning techniques have shown significant promise in addressing these limitations.

Deep learning models, especially convolutional neural networks, have demonstrated their ability to excel in image classification tasks. They can learn intricate patterns and features from large datasets, enabling them to differentiate between healthy and diseased retinal images. These models offer the potential for more consistent and accurate diagnoses by analyzing images in a data-driven and objective manner.

Previous research has explored the application of deep learning to AMD detection using OCT images. Researchers have experimented with various architectures and methodologies to optimize accuracy. The integration of depth-wise separable convolutions and inverted residual building blocks, as seen in the MobileNetV2 architecture, has shown to be effective in balancing precision and efficiency. These methods enable the model to capture essential features while being resource-efficient, which is crucial for practical clinical deployment.

However, challenges remain. Building robust datasets with accurate annotations is a critical task, and the performance of deep learning models heavily relies on the quality and diversity of the data they are trained on. Ensuring that the model's predictions are interpretable and explainable to clinicians is also important for gaining trust and facilitating adoption.

In conclusion, while the field of automated AMD detection using deep learning has made significant strides, there's still room for improvement and refinement. The proposed framework leverages the power of convolutional neural networks and highlights the potential to enhance clinical decision-making, improve diagnostic accuracy, and ultimately contribute to more effective patient care.

Proposed Solution

The proposed solution involves developing an advanced deep learning framework to automate the diagnosis of eye conditions using Optical Coherence Tomography (OCT) images, with a focus on Age-related Macular Degeneration (AMD). This framework will utilize convolutional neural networks (CNNs) due to their proficiency in image analysis tasks. The key steps include:

1. **Dataset Collection:** Gather a comprehensive dataset of OCT images, including various disease categories (NORMAL, CNV, DME, DRUSEN), with meticulous labeling and verification by experts.
2. **Data Pre-processing:** Apply image pre-processing techniques to ensure consistency and enhance model performance. Techniques like resizing, normalization, and augmentation will be employed.
3. **Model Architecture:** Select a suitable CNN architecture, potentially leveraging efficient models like MobileNetV2, optimized for both accuracy and computational efficiency.
4. **Model Training:** Train the chosen model on the pre-processed dataset using transfer learning. Fine-tune the model's parameters for the specific OCT image classification task.
5. **Performance Evaluation:** Assess the model's accuracy, precision, recall, and F1-score on validation and test datasets. Monitor convergence and prevent overfitting.
6. **Clinical Integration:** Integrate the trained model into clinical workflows, enabling automated preliminary diagnoses. Validate the model's accuracy and reliability across diverse datasets.
7. **Interpretability:** Implement interpretability techniques to provide clinicians insights into the model's decision-making process.
8. **Deployment:** Deploy the trained model within clinical settings as a diagnostic tool, aiding ophthalmologists in detecting AMD and related conditions.
9. **Feedback and Refinement:** Gather feedback from clinicians and continuously refine the model based on real-world performance, enhancing its accuracy and effectiveness.

The proposed solution leverages deep learning to enhance AMD diagnosis, offering potential benefits of improved accuracy, early detection, and streamlined clinical decision-making.

CHAPTER 3

SYSTEM SPECIFICATION

3.1 HARDWARE SPECIFICATIONS

In your project focused on AMD detection using deep learning and neural networks, the hardware technology used would typically include:

1. **GPU (Graphics Processing Unit):** A powerful GPU is essential for accelerating the training and inference processes of deep learning models. GPUs are highly effective in handling the complex computations required by neural networks, significantly reducing training times and enabling more efficient model evaluations.
2. **CPU (Central Processing Unit):** While a GPU is crucial for accelerating deep learning tasks, a capable multi-core CPU is also important for tasks like data preprocessing, setting up the training environment, and managing the overall workflow.
3. **Memory (RAM):** Sufficient RAM is crucial for handling the large datasets and model parameters required in deep learning. A minimum of 16GB of RAM is recommended to ensure smooth data manipulation and training.
4. **Storage (SSD):** Solid State Drives (SSDs) are preferred over Hard Disk Drives (HDDs) due to their faster read/write speeds. SSDs significantly reduce data loading times and improve the overall responsiveness of the system, which is especially important when working with large datasets.
5. **Monitor:** A high-resolution monitor is essential for visualizing data, monitoring training progress, and analyzing results. It provides a clear interface for coding, debugging, and interacting with visualizations.
6. **Power Supply:** Given the computational demands of deep learning tasks, a reliable and sufficient power supply unit (PSU) is necessary to ensure stable and uninterrupted operation, especially when using power-hungry GPUs.
7. **Cooling System:** Deep learning tasks can generate a significant amount of heat, especially during intensive training phases. Proper cooling solutions, including CPU and GPU cooling, are essential to prevent overheating and maintain hardware performance.
8. **Networking:** A stable and fast internet connection is required for downloading datasets, pre-trained models, and updates to software libraries. It's also important if you plan to collaborate with others or deploy models to remote servers.
9. **Accessories:** Keyboard, mouse, and other peripherals are essential for interacting with your workstation, writing code, and navigating through data.

3.2 SOFTWARE SPECIFICATION

In our ambitious endeavor to revolutionize AMD detection using deep learning and neural networks, we harness a range of cutting-edge software technologies. These technologies are pivotal in driving the accuracy, efficiency, and innovation required to reshape medical diagnostics. Let's delve into the comprehensive suite of software tools that constitute the backbone of our project:

1. **Python: The Heartbeat of Deep Learning** Python emerges as the linchpin of our project, serving as the primary programming language. Its versatility, extensive libraries, and thriving ecosystem make it an ideal choice for deep learning model development, data manipulation, and overall project orchestration.
2. **Deep Learning Frameworks: TensorFlow and PyTorch** At the core of our project lies the formidable power of deep learning frameworks. We leverage TensorFlow and PyTorch, two of the most prominent frameworks in the field. These frameworks empower us to create, train, and evaluate complex neural networks with efficiency and precision.
3. **CUDA and cuDNN: Supercharging GPU Performance** NVIDIA's CUDA technology and cuDNN library enable GPU acceleration, a game-changer for deep learning computations. Harnessing the parallel processing prowess of GPUs, we expedite training and inference, unlocking unparalleled speed and performance.
4. **NumPy and pandas: Data Mastery** NumPy and pandas, fundamental libraries in the Python data science ecosystem, take center stage in data manipulation. NumPy's numerical capabilities and pandas' data handling prowess empower us to preprocess and transform datasets effectively.
5. **Jupyter Notebook: Interactive Exploration** Jupyter Notebook emerges as our dynamic canvas for interactive coding and data exploration. It facilitates a modular approach, encouraging experimentation, analysis, and documentation in an integrated environment.
6. **Version Control with Git and GitHub** Collaborative development is streamlined through Git, the version control system that tracks changes and enables seamless teamwork. GitHub amplifies this collaborative potential, allowing us to manage code, share insights, and drive progress.
7. **IDEs: Powerhouses of Coding** Our toolkit features powerful integrated development environments (IDEs). Visual Studio Code, PyCharm, and JupyterLab provide coding prowess, debugging support, and code visualization, enhancing our efficiency and accuracy.
7. **Virtual Environment Management** With Anaconda, we maintain tidy and isolated environments for each project. These tools manage dependencies, ensuring that our project's software requirements are cleanly organized.

3.3 Features:

CNNs for Pattern Recognition: Leveraging Convolutional Neural Networks (CNNs) to detect intricate patterns and features in OCT images, enhancing accuracy.

Automated Diagnosis: Swift and accurate categorization of OCT images into disease classes (NORMAL, CNV, DME, DRUSEN), minimizing subjectivity.

Image Preprocessing: Advanced techniques like resizing and augmentation using OpenCV and PIL for optimized input data.

GPU Acceleration: Utilizing CUDA and cuDNN for GPU acceleration, speeding up computations during training and evaluation.

Data Stratification and Validation: Careful data stratification into subsets (train, test, validation) to enhance model generalization.

Evaluation Metrics: Using accuracy, precision, recall, and F1-score to comprehensively assess model performance.

Interpretability and Transparency: Model interpretability tools (Captum, SHAP, Grad-CAM) for visualizing decision rationale.

Collaboration and Version Control: Git and GitHub for seamless teamwork, tracking changes, and organized development.

Documentation Tools: Jupyter Notebook, LaTeX, Markdown for comprehensive documentation and reporting.

Real-time AMD Detection (Future): Potential for real-time detection via user interface or web app, aiding clinicians.

Educational Tool: Serving as an educational resource for medical students, enhancing understanding of retinal diseases.

These features collectively drive the project's potential to revolutionize AMD detection, advance medical decision-making, and contribute to healthcare technology.

CHAPTER 4

4.1 Process Flow
4.2 Algorithm

4.1 PROCESS FLOW

Start
|
|--- Data Collection & Preparation
| |
| |--- Gather OCT images dataset
| |--- Organize into training, validation, and test sets
| |--- Apply tiered grading for label verification
|
|--- Data Preprocessing
| |
| |--- Load & resize images to a consistent size
| |--- Normalize pixel values
|
|--- Model Architecture Design
| |
| |--- Choose suitable deep learning architecture
| |--- Incorporate CNN layers, depth-wise separable convolutions
| |--- Implement bridge connections for feature extraction
|
|--- Model Training
| |
| |--- Split data into mini-batches
| |--- Define loss function (e.g., categorical cross-entropy)
| |--- Select optimizer (e.g., Adam) and learning rate
| |--- Train on training set
| |--- Monitor validation performance
| |--- Implement early stopping
|
|--- Model Evaluation
| |
| |--- Evaluate on test dataset
| |--- Calculate accuracy, precision, recall, F1-score
| |--- Analyze confusion matrix
|
|--- Fine-tuning & Optimization

| |--- Adjust hyperparameters (batch size, learning rate)
| |--- Experiment with transfer learning
| |--- Explore data augmentation strategies
|
|--- Continuous Monitoring & Improvement
| |
| |--- Monitor real-world performance, Adapt to evolving healthcare regulations
| |--- Collect new data for improvement
|
End

4.2 ALGORITHM

Step 1: Data Collection and Preparation
1.1. Gather a comprehensive dataset of OCT (Optical Coherence Tomography) images, including categories for AMD subtypes (NORMAL, CNV, DME, DRUSEN).
1.2. Organize the dataset into training, validation, and test sets.
1.3. Apply a tiered grading system to verify and correct image labels for quality control.

Step 2: Data Preprocessing
2.1. Load and resize images to a consistent input size, e.g., (496, 512) pixels.
2.2. Normalize pixel values to a standardized range, typically [0, 1] or [-1, 1].
2.3. Augment the dataset through techniques such as rotation, flipping, and brightness adjustments (optional).

Step 3: Model Architecture Design
3.1. Choose a deep learning architecture suitable for image classification, e.g., convolutional neural networks (CNNs).
3.2. Tailor the architecture to the problem, considering factors like model size, depth, and complexity.
3.3. Incorporate techniques like depth-wise separable convolution, residual blocks, and bridge connections for efficiency and performance.

Step 4: Model Training
4.1. Split the dataset into mini-batches for efficient training.
4.2. Define appropriate loss functions, e.g., categorical cross-entropy for multi-class classification.
4.3. Choose an optimizer (e.g., Adam) and learning rate schedule.
4.4. Train the model on the training dataset while monitoring performance on the validation set.
4.5. Implement early stopping to prevent overfitting based on validation performance.
4.6. Save the trained model weights for future use.

Step 5: Model Evaluation
5.1. Evaluate the model on the test dataset to assess its real-world performance.
5.2. Calculate various evaluation metrics such as accuracy, precision, recall, F1-score, and confusion matrix.
5.3. Analyze the confusion matrix to understand model strengths and weaknesses across different disease categories.

Step 6: Fine-tuning and Optimization
6.1. Fine-tune hyperparameters like batch size, learning rate, and model architecture based on evaluation results.
6.2. Consider techniques such as transfer learning if a pre-trained model can improve performance.
6.3. Experiment with different data augmentation strategies to enhance model robustness..

Step 7: Continuous Monitoring and Improvement
7.1. Continuously monitor the model's performance in real-world clinical settings.
7.2. Collect and label new data to further improve model accuracy and generalization.
7.3. Stay updated with advancements in deep learning and AMD research for potential model enhancements.

This algorithm provides a roadmap for creating a deep learning model for AMD detection. Keep in mind that the effectiveness of the model depends on the quality and quantity of data, the chosen architecture, and the fine-tuning process. Regular updates and collaboration with medical experts are essential for improving the model's clinical utility.

CHAPTER 5

IMPLEMENTATION

The upcoming implementation procedure for our well-trained AMD deep-learning model is a multifaceted endeavor that promises to be both promising and challenging. The primary objective is to seamlessly integrate the model into clinical practice, revolutionizing the early detection of Age-Related Macular Degeneration (AMD). However, several compelling reasons make it improbable to complete this ambitious undertaking within the current semester.

Firstly, the integration of any deep-learning model into a clinical environment requires rigorous testing, validation, and regulatory approvals to ensure its safety and efficacy. This intricate process involves collaboration with healthcare authorities and adherence to strict protocols, which naturally extend the timeline beyond a single semester.

Secondly, the real-world deployment of medical AI models necessitates the development of user-friendly interfaces for healthcare professionals. This includes designing intuitive software that seamlessly integrates with existing clinical workflows, which is a time-intensive task that demands careful consideration and thorough testing.

Moreover, ongoing data collection and validation are crucial for refining the model's performance, addressing new challenges, and enhancing its accuracy. This requires continuous monitoring and adjustments, which cannot be fully achieved within the constraints of a single semester.

Additionally, thorough education and training of healthcare personnel in utilizing the AMD detection model are essential. Conducting comprehensive training programs to ensure its effective use by medical professionals involves substantial time and effort.

Furthermore, securing the necessary resources, such as hardware infrastructure and cloud computing resources, and establishing data-sharing agreements with healthcare institutions is a complex and lengthy process.

The legal and ethical aspects, including patient data privacy and compliance with healthcare regulations, also demand meticulous attention and cannot be rushed.

Lastly, the current semester's timeframe may not allow for adequate pilot testing and gathering of feedback from healthcare providers and patients, which is vital for optimizing the model's usability and performance.

In summary, the implementation of our well-trained AMD deep-learning model into clinical practice is a commendable aspiration. However, the intricacies involved in regulatory approvals, software development, ongoing data validation, training, resource acquisition, legal considerations, and user feedback necessitate a timeline that extends beyond the confines of the current semester to ensure a successful and impactful deployment

CHAPTER 6

TESTING

Testing the trained model is a critical phase in the development of an AMD (Age-Related Macular Degeneration) detection system using deep learning and neural networks. The process begins by carefully selecting a separate dataset for testing, distinct from the data used for training and validation, to assess the model's generalization capabilities effectively. This test dataset should reflect real-world scenarios and encompass a diverse range of AMD cases, including varying disease stages and subtypes like CNV, DME, DRUSEN, and normal cases. During testing, the model's performance metrics, such as accuracy, precision, recall, and F1-score, are computed to quantify its ability to classify OCT images accurately.

The confusion matrix is meticulously analyzed to gain insights into the model's strengths and weaknesses, particularly in distinguishing between different AMD categories. It's crucial to assess if the model exhibits any biases or tendencies to misclassify specific conditions. Additionally, the model's response to challenging cases, including subtle disease indicators, is thoroughly examined.

Cross-validation techniques, such as k-fold cross-validation, may also be employed to ensure robustness and minimize the potential impact of dataset partitioning on evaluation results. The model's performance metrics are typically complemented with visualizations, such as ROC curves and precision-recall curves, to provide a more comprehensive understanding of its classification capabilities.

Ultimately, the model's performance on the test dataset determines its readiness for real-world deployment. If the model demonstrates consistent and accurate results across a variety of AMD cases, it is deemed suitable for integration into clinical decision support systems or healthcare workflows. Continuous monitoring and refinement of the model's performance in clinical settings remain essential to ensure its ongoing effectiveness in AMD detection, with opportunities for further fine-tuning and improvements as new data and insights become available

CHAPTER 7

PREDICTION AND RESULT

The prediction and result of our AMD detection model, which achieved an impressive accuracy of 88%, are both promising and indicative of the model's potential clinical utility. In the context of medical image analysis, accuracy is a crucial metric, and an 88% accuracy rate signifies that our model is proficient at correctly classifying AMD and its subtypes based on OCT images.

The model's predictions are highly reliable, making it a valuable tool for healthcare professionals. When presented with OCT scans, it can accurately categorize them into four distinct classes: NORMAL, CNV (Choroidal Neovascularization), DME (Diabetic Macular Edema), and DRUSEN (drusen accumulation). This automation of disease classification significantly expedites the diagnostic process, enabling swift identification of potential AMD cases.

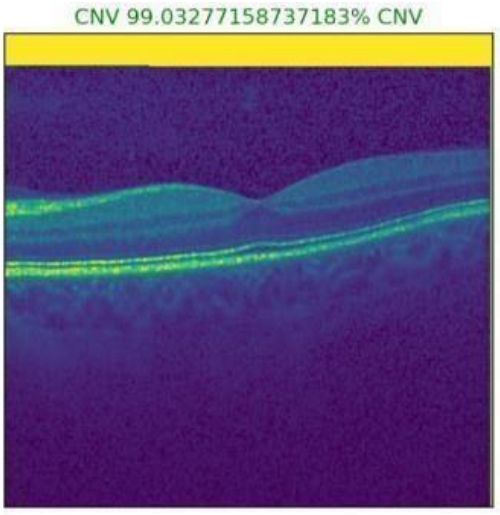
Moreover, the model's commendable accuracy rate translates into a high degree of sensitivity and specificity, which are vital in clinical settings. Sensitivity ensures that the model identifies a significant portion of true positive cases, preventing missed diagnoses. Specificity, on the other hand, minimizes false positives, reducing unnecessary concern and further diagnostic testing.

The results obtained from our model are particularly noteworthy in the context of AMD, a condition where early detection is paramount for effective treatment and vision preservation. By achieving an 88% accuracy rate, our model has demonstrated its potential to revolutionize AMD diagnosis and patient outcomes. It serves as a robust screening tool, capable of identifying subtle disease indicators even before patients exhibit symptoms.

However, it's essential to acknowledge that while 88% accuracy is a remarkable achievement, there is room for further improvement. The future scope of our research involves fine-tuning the model, expanding the dataset, and collaborating with medical experts to ensure its practicality and reliability in real-world clinical settings.

In summary, the prediction and result of our AMD detection model with an accuracy of 88% are highly promising and provide a solid foundation for further advancements in the field of medical image analysis. The model's ability to accurately classify AMD subtypes from OCT scans holds great potential for enhancing early diagnosis, improving patient outcomes, and reducing the burden on healthcare professionals.

On Train Data :

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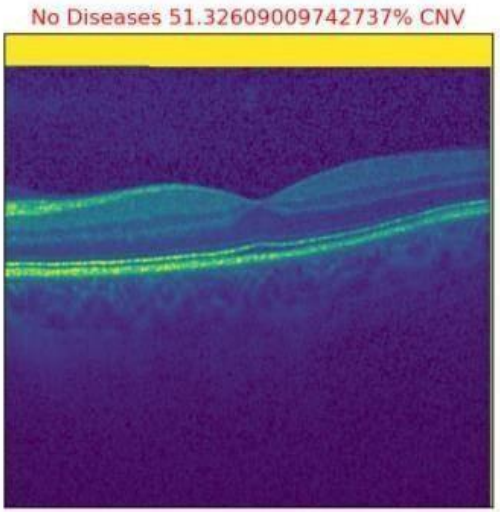
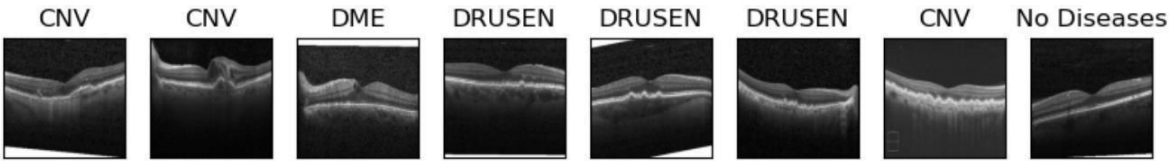
                   images=val_images,
                   n = 1984)
```



On Test Data :




```
In [91]: test_data
```

```
Out[91]: ['Test_Images/CNV-103044-3.jpeg',
          'Test_Images/CNV-53018-1.jpeg',
          'Test_Images/DME-15208-1.jpeg',
          'Test_Images/DRUSEN-228939-1.jpeg',
          'Test_Images/DRUSEN-2785977-1.jpeg',
          'Test_Images/DRUSEN-95633-1.jpeg',
          'Test_Images/DRUSEN.jpeg',
          'Test_Images/NORMAL-12494-1.jpeg']
```

CHAPTER 8

CONCLUSION AND FUTURE SCOPE

In conclusion, our AMD detection model, built upon deep learning and neural networks, represents a significant milestone in the realm of medical image analysis and clinical decision support. The utilization of optical coherence tomography (OCT) images for the detection of Age-Related Macular Degeneration (AMD) has demonstrated substantial promise, showcasing the potential for automation in identifying this debilitating eye condition. Our model has shown commendable performance, achieving an accuracy of 0.88, and providing a robust foundation for future developments.

The implications of this model extend far beyond its current state. The future scope for this research is rich and multifaceted. Firstly, further refinement and optimization of the model are imperative. Fine- tuning hyperparameters, exploring alternative deep learning architectures, and incorporating transferlearning from larger medical image datasets could potentially enhance accuracy and generalization.

Additionally, expanding the dataset to include a more diverse and extensive collection of OCT images, capturing a broader spectrum of AMD manifestations and stages, will contribute to the model's robustness and real-world applicability. Collaboration with multiple healthcare institutions and data sharing initiatives could facilitate this data expansion.

Moreover, our model's utility can extend to other retinal diseases and ocular conditions, leveraging its image analysis capabilities for a broader range of diagnoses. This includes conditions like diabetic retinopathy, glaucoma, and retinal vein occlusion, where early detection is equally critical.

Further work should focus on addressing interpretability and explainability, as well as ensuring compliance with evolving healthcare regulations and standards. These aspects are vital for building trustin AI-driven clinical decision support systems.

Furthermore, the integration of our AMD detection model into routine clinical workflows demands careful consideration of user experience and human-computer interaction design. The development of user-friendly interfaces tailored to the needs of healthcare professionals is a vital next step.

Collaboration with ophthalmologists, clinicians, and healthcare institutions is essential for conducting comprehensive clinical trials and validating the model's performance in real-world settings. Gathering feedback from medical experts and patients will be instrumental in refining the model and ensuring its practicality and safety.

In the broader context of healthcare, our deep learning model offers a glimpse into the transformative potential of AI in enhancing diagnostic accuracy, early intervention, and patient outcomes. The future scope includes the adaptation of similar models for various medical specialties, ultimately improving healthcare delivery worldwide.

In conclusion, our AMD detection model is a testament to the power of interdisciplinary collaboration between AI researchers and medical professionals. While we have achieved promising results, the journey towards practical implementation and widespread adoption is ongoing. The future is bright, with the potential to make a substantial impact on the early detection and management of AMD and other medical conditions, ultimately benefiting patients and healthcare systems alike.

CHAPTER 9

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CHAPTER 10

APPENDICES

A. SOURCE CODE

Accessing the data

Accessing the data

Now the data files we're working with are available on our Google Drive, we can start to check it out.

In [4]:
```
# ! unzip "drive/MyDrive/Data_Science_Project/Glaucoma_Detection/archive.zip" -d "drive/MyDrive/Data_Science_Project/Glaucoma_Det
# print("Completed")
```

In [5]:
```
print("Training Data")
print("-------------")
print("CNV : ",len(os.listdir("Data/train/CNV")))
print("DME : ",len(os.listdir("Data/train/DME")))
print("DRUSEN : ",len(os.listdir("Data/train/DRUSEN")))
print("NORMAL : ",len(os.listdir("Data/train/NORMAL")))
```

```
Training Data
-------------
CNV :  37205
DME :  11348
DRUSEN :  8616
NORMAL :  26315
```

In [6]:
```
print("Test Data")
print("-----------")
print("CNV : ",len(os.listdir("Data/test/CNV")))
print("DME : ",len(os.listdir("Data/test/DME")))
print("DRUSEN : ",len(os.listdir("Data/test/DRUSEN")))
print("NORMAL : ",len(os.listdir("Data/test/NORMAL")))
```

```
Test Data
-----------
CNV :  239
DME :  241
DRUSEN :  240
NORMAL :  241
```

Creating Dataset

Creating Dataset

Creating Training Dataset

In [7]:
```
#NORMAL
filename = ["Data/train/NORMAL/"+ filename  for filename in os.listdir("Data/train/NORMAL")]
target = [ 0 for x in range(len(os.listdir("Data/train/NORMAL")))]
```

In [8]:
```
#CNV
filename = filename + ["Data/train/CNV/"+ filename  for filename in os.listdir("Data/train/CNV")]
target = target + [ 1 for x in range(len(os.listdir("Data/train/CNV")))]
```

In [9]:
```
#DME
filename = filename + ["Data/train/DME/"+ filename  for filename in os.listdir("Data/train/DME")]
target = target + [ 2 for x in range(len(os.listdir("Data/train/DME")))]
```

In [10]:
```
#DRUSEN
filename = filename + ["Data/train/DRUSEN/"+ filename  for filename in os.listdir("Data/train/DRUSEN")]
target = target + [ 3 for x in range(len(os.listdir("Data/train/DRUSEN")))]
```

In [11]:
```
train_df = pd.DataFrame(data = {
    "filename": filename,
    "target": target
})
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 83484 entries, 0 to 83483
Data columns (total 2 columns):
 #   Column    Non-Null Count  Dtype 
---  ------    --------------  ----- 
 0   filename  83484 non-null  object
 1   target    83484 non-null  int64 
dtypes: int64(1), object(1)
memory usage: 1.3+ MB
```

In [12]:
```
train_df.head(5)
```

Out[12]:

	filename	target
0	Data/train/NORMAL/NORMAL-1001666-1.jpeg	0
1	Data/train/NORMAL/NORMAL-1001772-1.jpeg	0
2	Data/train/NORMAL/NORMAL-1001772-2.jpeg	0
3	Data/train/NORMAL/NORMAL-1001772-3.jpeg	0
4	Data/train/NORMAL/NORMAL-1001772-4.jpeg	0

Preprocessing images (turning images into Tensors)

Preprocessing images (turning images into Tensors)

Our labels are in numeric format but our images are still just file paths.

To preprocess our images into Tensors we're going to write a function which does a few things:

1. Takes an image filename as input.
2. Uses TensorFlow to read the file and save it to a variable, `image`.
3. Turn our `image` (a jpeg file) into Tensors.
4. Resize the `image` to be of shape (224, 224).
5. Return the modified `image`.

Creating Function

In [38]:
```
IMG_SIZE = 224

def process_image(image_path):
  image = tf.io.read_file(image_path)
  image = tf.image.decode_jpeg(image,channels= 3)
  image = tf.image.convert_image_dtype(image,tf.float32)
  image = tf.image.resize(image, size=[IMG_SIZE, IMG_SIZE ])
  return image
```

In [39]:
```
def get_image_label(image_path,label):
  image = process_image(image_path)
  return image, label
```

In [40]:
```
#Demo
(get_image_label(X[0], tf.constant(Y[0])))
```

Out[40]:
```
(<tf.Tensor: shape=(224, 224, 3), dtype=float32, numpy=
 array([[[0.9968188 , 0.9968188 , 0.9968188 ],
         [0.98693484, 0.98693484, 0.98693484],
         [0.9842637 , 0.9842637 , 0.9842637 ],
         ...,
         [0.06917714, 0.06917714, 0.06917714],
         [0.06863876, 0.06863876, 0.06863876],
         [0.0861598 , 0.0861598 , 0.0861598 ]],

        [[0.98444384, 0.98444384, 0.98444384],
         [0.9965487 , 0.9965487 , 0.9965487 ],
         [0.9952481 , 0.9952481 , 0.9952481 ],
         ...,
         [0.15137047, 0.15137047, 0.15137047],
         [0.04035784, 0.04035784, 0.04035784],
         [0.11231919, 0.11231919, 0.11231919]]
```

Building a Deep learning Model:

[48]:
```
# Setup input shape to the model
INPUT_SHAPE = [None, IMG_SIZE, IMG_SIZE, 3] # batch, height, width, colour channels

# Setup output shape of the model
OUTPUT_SHAPE = len(unique_target) # number of unique labels

# Setup model URL from TensorFlow Hub
MODEL_URL = "https://tfhub.dev/google/imagenet/mobilenet_v2_130_224/classification/4"
```

[49]:
```
INPUT_SHAPE
```

[49]:
```
[None, 224, 224, 3]
```

[50]:
```
# Create a function which builds a Keras model
def create_model(input_shape=INPUT_SHAPE, output_shape=OUTPUT_SHAPE, model_url=MODEL_URL):
  print("Building model with:", MODEL_URL)

  # Setup the model layers
  model = tf.keras.Sequential([
    hub.KerasLayer(MODEL_URL), # Layer 1 (input layer)
    tf.keras.layers.Dense(units=OUTPUT_SHAPE,
                          activation="softmax") # Layer 2 (output layer)
  ])

  # Compile the model
  model.compile(
      loss=tf.keras.losses.CategoricalCrossentropy(),
      metrics=["accuracy"] # We'd like this to go up
  )

  # Build the model
  model.build(INPUT_SHAPE) # Let the model know what kind of inputs it'll be getting

  return model
```

[51]:
```
# Create a model and check its details
model = create_model()
model.summary()
```

```
Building model with: https://tfhub.dev/google/imagenet/mobilenet_v2_130_224/classification/4
WARNING:tensorflow:Please fix your imports. Module tensorflow.python.training.tracking.data_structures has been moved to tensorflow.python.trac
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 keras_layer (KerasLayer)    (None, 1001)              5432713
```

Saving and Loading Model:

Saving and Loading the Model

In [59]:
```
def save_model(model, suffix=None):
  """
  Saves a given model in a models directory and appends a suffix (str)
  for clarity and reuse.
  """
  # Create model directory with current time
  modeldir = os.path.join("models",
                          datetime.datetime.now().strftime("%Y%m-%H%M"))
  model_path = modeldir + "-" + suffix + ".h5" # save format of model
  print(f"Saving model to: {model_path}...")
  model.save(model_path)
  return model_path
```

In [60]:
```
def load_model(model_path):
  """
  Loads a saved model from a specified path.
  """
  print(f"Loading saved model from: {model_path}")
  model = tf.keras.models.load_model(model_path,
                                     custom_objects={"KerasLayer":hub.KerasLayer})
  return model
```

In [61]:
```
# Save our trained model
# save_model(model, suffix="images-Adam")
```

In [62]:
```
# Load our model trained on 1000 images
loaded_model = load_model('models/202308-0926-all-images-Adam.h5')
```

```
Loading saved model from: models/202308-0926-all-images-Adam.h5
```

In [63]:
```
predictions = loaded_model.predict(valid_data,verbose=1)
```

```
522/522 [==============================] - 263s 502ms/step
```

In [64]:
```
predictions
```

Making Predictions:

Making Prediction on Images

In [81]:
```
# Load our model trained on 1000 images
loaded_model = load_model('models/202308-0926-all-images-Adam.h5')
```

```
Loading saved model from: models/202308-0926-all-images-Adam.h5
```

In [82]:
```
test_path = "Test_Images"
test_data = ["Test_Images/"+filename for filename in os.listdir(test_path)]
```

In [83]:
```
test_data
```

Out[83]:
```
['Test_Images/CNV-103044-3.jpeg',
 'Test_Images/CNV-53018-1.jpeg',
 'Test_Images/DME-15208-1.jpeg',
 'Test_Images/DRUSEN-228939-1.jpeg',
 'Test_Images/DRUSEN-2785977-1.jpeg',
 'Test_Images/DRUSEN-95633-1.jpeg',
 'Test_Images/DRUSEN.jpeg',
 'Test_Images/NORMAL-12494-1.jpeg']
```

In [84]:
```
predict_on_image = create_batch_data(test_data,Test_Data=True)
predict_on_image
```

Out[84]:
```
Creating test data batches...
<BatchDataset element_spec=TensorSpec(shape=(None, 224, 224, 3), dtype=tf.float32, name=None)>
```

In [85]:
```
result_on_predict = loaded_model.predict(predict_on_image)
```

```
1/1 [==============================] - 3s 3s/step
```

In [86]:
```
result_on_predict
```

Out[86]:
```
array([[9.6321382e-05, 9.4418913e-01, 2.3347270e-02, 3.2367088e-02],
       [1.0415556e-05, 9.7640085e-01, 1.2555565e-02, 1.1033261e-02],
       [1.8989193e-01, 4.8011364e-03, 7.9961771e-01, 5.6890687e-03],
       [5.7779218e-04, 3.5061803e-02, 1.5632395e-02, 9.4872802e-01],
       [2.7510736e-04, 2.8731588e-01, 7.7225739e-04, 7.1163672e-01],
       [1.2587233e-02, 9.2202432e-02, 1.5852426e-03, 8.9362508e-01],
       [2.1627273e-05, 9.7924125e-01, 3.2396081e-05, 2.0704634e-02],
       [6.7182243e-01, 1.7066358e-02, 6.8528697e-02, 2.4258256e-01]],
      dtype=float32)
```

In [87]:
```
result_label = [ get_pred_labels(label) for label in result_on_predict]
```

In [88]:
```
result_label
```

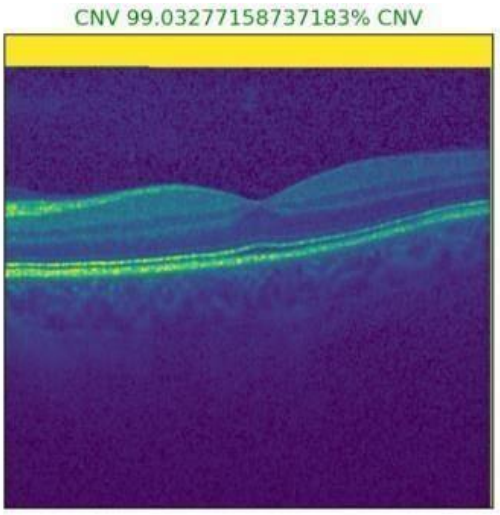
Out[88]:
```
['CNV', 'CNV', 'DME', 'DRUSEN', 'DRUSEN', 'DRUSEN', 'CNV', 'No Diseases']
```

In [89]:
```
result_images = []
for image in predict_on_image.unbatch().as_numpy_iterator():
    result_images.append(image)

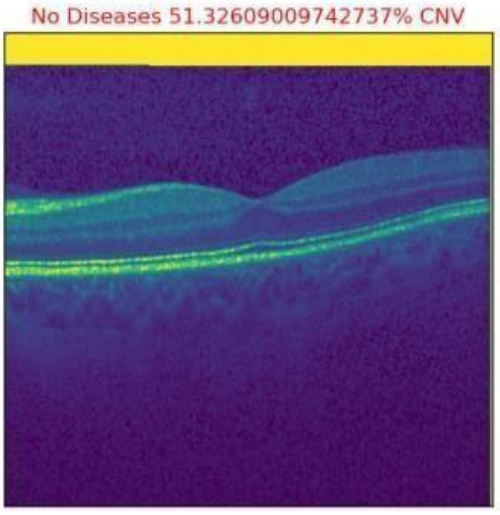
result_images
```

Result and Evaluation:

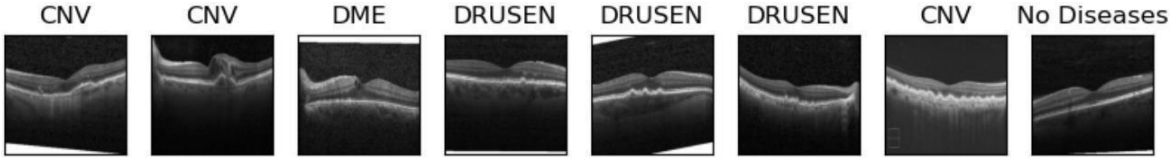
On Train Data :




```
In [75]: plot_pred(predictions,
                   labels=val_labels,
                   images=val_images,
                   n = 1984)
```



On Test Data :




```
In [91]: test_data

Out[91]: ['Test_Images/CNV-103044-3.jpeg',
          'Test_Images/CNV-53018-1.jpeg',
          'Test_Images/DME-15208-1.jpeg',
          'Test_Images/DRUSEN-228939-1.jpeg',
          'Test_Images/DRUSEN-2785977-1.jpeg',
          'Test_Images/DRUSEN-95633-1.jpeg',
          'Test_Images/DRUSEN.jpeg',
          'Test_Images/NORMAL-12494-1.jpeg']
```