

# **Second year Mini Project Report**

Submitted in partial fulfillment of the requirements of the degree

## **BACHELOR OF ENGINEERING IN COMPUTER ENGINEERING**

### **FETAL ABNORMALITIES DETECTION**

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# CERTIFICATE

This is to certify that the Mini Project entitled **Fetal Abnormalities Detection** is a bonafide work of **Vivek Venkatachalam (63), Vaishnavi Sonawane (58), Gouresh Madye (39), Nishika Gangwani (24), Aryan Surve (67)** submitted to the University of Mumbai in partial fulfillment of the requirement for the award of the degree of **“Bachelor of Engineering”** in **“Computer Engineering”**.

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Principal

# Mini Project Approval

This Mini Project entitled **Fetal Abnormalities Detection** by **Vivek Venkatachalam (63), Vaishnavi Sonawane (58), Gouresh Madye (39), Nishika Gangwani (24), Aryan Surve (67)** is approved for the degree of **Bachelor of Engineering in Computer Engineering**.

## Examiners

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(External Examiner name & Sign)

Date:

Place:

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## **ABSTRACT**

The increasing rates of neurodevelopmental disorders (NDs) are threatening pregnant women, parents, and clinicians caring for healthy infants and children. NDs can initially start through embryonic development due to several reasons. Up to three in 1000 pregnant women have embryos with brain defects. Ensuring the well-being of the fetus throughout pregnancy is paramount for effective prenatal care, necessitating the early detection of any potential health disorders. However, conventional methods of monitoring fetal health, such as periodic ultrasound scans and clinical assessments, often suffer from limitations in providing real-time and continuous monitoring.

To overcome these challenges, this research presents an innovative framework that harnesses the power of artificial intelligence (AI) algorithms for the early detection of fetal health disorders. Central to our approach is the development of a Foetal Health Disorder Detector, which leverages cutting-edge AI technologies. Our focus lies in analyzing fetal brain ultrasound images, as the fetal brain's development during the second trimester is crucial and abnormalities can have significant implications. By utilizing a Convolutional Neural Network (CNN) model, we propose a sophisticated classification system capable of accurately identifying fetal health status with an impressive accuracy rate of 77.87%.

The significance of our research lies in its potential to revolutionize prenatal care by introducing a proactive and precise method for detecting fetal abnormalities at an early stage. By providing clinicians with timely and accurate information, our framework aims to enhance maternal and fetal health outcomes, ultimately contributing to improved prenatal care practices and better overall pregnancy outcomes.

## ACKNOWLEDGEMENT

We would like to express our sincere gratitude to several individuals and organizations for supporting me throughout our Project.

We would like to express my sincere appreciation and gratitude to our HOD **Mrs. Nupur Giri** and our Mentor **Mrs. Nusrat Ansari** for their guidance, expertise, and continuous encouragement throughout the project. Your insights and advice have been instrumental in shaping this work. We are highly indebted to our mentor for their guidance and constant supervision as well as for providing necessary information regarding the project and also for their support in completing the project. We would like to express our gratitude towards our parents for their kind cooperation and encouragement which would express our special gratitude.

Each of us has contributed effort for doing this project and it would have not been possible without kindness and support. We would like to convey our heartfelt gratitude to Mrs Nusrat Ansari, our mentors, for their invaluable advice and assistance in completing my project. They were there to assist our Group Project in every step of the way, and their motivation is what enabled us to accomplish our task effectively. We would also like to thank all of the other supporting personnel who assisted us by supplying the equipment that was essential and vital, without which we would not have been able to perform efficiently on this project.

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We express our sincere gratitude to our mentor Mrs. Nusrat Ansari Ma'am for her invaluable guidance and unwavering support throughout this research project. Her expertise and encouragement played a pivotal role in shaping our work from conceptualization to the final stages of the paper. Mrs. Ansari Ma'am not only shared her extensive knowledge but also challenged us to think critically and push the boundaries of our research

Our thanks and appreciation also go to our colleagues developing the project and people who have willingly helped us out with their abilities.

### Abbreviations :

- ENDS - Embryonic Neurodevelopmental Disorders
- Deep Neural Network (DNN)
- Deep Hybrid Learning (DHL)
- ADHD - Attention-Deficit/Hyperactivity Disorder
- IVF - In Vitro Fertilization
- NDs - Neurodevelopmental Disorders.

# CHAPTER 1

## INTRODUCTION

### 1.1 Introduction:

Fetal Abnormalities Detection using Machine Learning (ML) holds significant promise in revolutionizing prenatal care by leveraging ultrasound imaging technology. This mini-project aims to delve into the realm of fetal health assessment through advanced computational techniques. Previous research in this domain has laid foundational groundwork, showcasing ML's potential in discerning abnormalities from ultrasound images with remarkable accuracy and efficiency. Studies have highlighted the efficacy of various ML algorithms in identifying diverse fetal anomalies, ranging from structural deformities to genetic disorders. However, amidst these advancements, several questions arise, compelling further exploration and refinement. How can ML algorithms be optimized to handle the complexity and variability inherent in ultrasound images? What are the ethical implications surrounding the integration of AI technology into prenatal diagnostics? How can we ensure accessibility and affordability of such advanced diagnostic tools to a diverse demographic

The significance of this study lies in its potential to address critical gaps in prenatal healthcare. By enhancing the early detection of fetal abnormalities, we aim to facilitate timely interventions, thereby improving clinical outcomes and enhancing the overall quality of care for expectant parents and their unborn children. Additionally, this research endeavors to contribute to the burgeoning field of AI-enabled healthcare, fostering interdisciplinary collaborations and driving innovation in the pursuit of safer and more effective prenatal diagnostics.

**Congenital disorders** encompass structural or functional anomalies that arise during fetal development, commonly known as birth defects, congenital anomalies, or congenital malformations. These conditions may manifest before birth, at birth, or later in life. Approximately 6% of newborns worldwide are affected by congenital disorders, leading to hundreds of thousands of related fatalities. These disorders likely result from a combination of genetic, biological, psychosocial and environmental risk factors. A broad range of environmental risk factors may affect neurodevelopment, including (but not limited to) maternal use of alcohol, tobacco, or illicit drugs during pregnancy; lower socioeconomic status; preterm birth; low birthweight; the physical environment; and prenatal or childhood exposure to certain environmental contaminants.

So, in order to detect disorders, we are implementing Convolutional Neural Networks (CNNs) due to their proficiency in analyzing visual data such as ultrasound images. CNNs excel at capturing hierarchical features within images, which is essential for identifying subtle abnormalities in fetal scans. Utilizing CNNs allows us to extract intricate patterns and features from ultrasound images, enabling accurate classification of various fetal anomalies.

## **1.2 Motivation:**

The motivation behind this project on embryonic neurodevelopmental disorders is rooted in the following points-

### **Clinical Impact:**

Embryonic neurodevelopment disorders are a critical area of concern, as they can have profound and lifelong consequences for affected individuals. These disorders encompass a wide range of conditions, including neural tube defects, intellectual disabilities, and neurodevelopmental disorders. Addressing these conditions is essential for the well-being of individuals and their families.

### **Lack of Understanding:**

Embryonic neurodevelopment disorders remain poorly understood in many aspects. There is a need for more research to unravel the genetic, environmental, and molecular factors that contribute to these disorders. A better understanding can lead to improved prevention, diagnosis, and treatment strategies.

### **Clinical Challenges:**

Medical professionals and researchers face challenges in the diagnosis, early intervention, and treatment of embryonic neurodevelopment disorders. This project seeks to alleviate these challenges by contributing to the development of more effective diagnostic tools and therapeutic interventions.

### **Impact on Families:**

Embryonic neurodevelopment disorders often have a significant impact on the emotional, psychological, and financial well-being of affected individuals and their families. The project is motivated by the desire to lessen this burden by contributing to better diagnostic and therapeutic options.

### **Value of Life :**

The project's motivation is deeply rooted in the goal of improving the quality of life for individuals affected by embryonic neurodevelopment disorders. By enhancing our understanding and facilitating early diagnosis and intervention, we can help individuals reach their full potential and lead fulfilling lives.



### **1.3 Problem Statement & Objectives:**

To find accurate and timely diagnosis of Fetal Neurodevelopment Disorders remains a challenge due to the complexity of the underlying biological processes such as it is hard to detect the stage of fetus as it moves and the lack of efficient tools for early detection.

**Objectives:-** Early Detection and Diagnosis, Risk Assessment, Genetic considerations, Scientific Advancement. The goal is to train a Convolutional Neural Network (CNN) to accurately predict whether a given image of the fetal is healthy or unhealthy .

### **1.4 Organization of the Report:**

The introduction section of the report provides a comprehensive overview of neurodevelopmental disorders, elucidating their profound impact and the driving motivations behind undertaking the project. Within this section, the problem statement is clearly articulated, and specific objectives for the study are delineated. Following this, the literature survey section critically evaluates existing research on neurodevelopmental disorders, highlighting gaps in the literature and underscoring the significance of the proposed project's contributions to the field. Moving forward, the proposed system section elaborates on the innovative approach to data summarization within the realm of embryonic neurodevelopmental disorders. This section delves into the system's architecture, algorithmic design, hardware and software prerequisites, experimental findings, and prospects for future research endeavors. Finally, the references section meticulously catalogs all sources and references utilized throughout the report, facilitating further exploration and verification of the documented findings and assertions.

## **CHAPTER 2**

### **LITERATURE SURVEY**

#### **Paper 1 : Deep Hybrid Learning Method for Classification of Fetal Brain Abnormalities**

The study focuses on early detection of fetal brain abnormalities using MRI, crucial for managing high-risk pregnancies. Manual analysis of MRI images is prone to misclassification and is time-consuming. Deep learning techniques offer efficient alternatives but face challenges like computational complexity and overfitting. To address these, a Deep Hybrid Learning (DHL) method, combining deep learning with machine learning, is proposed. Experimental results demonstrate improved classification accuracy with DHL, particularly with a DNN+RF model. Future research aims to explore modified deep learning techniques and incorporate real-time datasets for further enhancement.

Limitation:

The proposed Deep Hybrid Learning (DHL) method for classifying fetal brain abnormalities using MRI images has limitations. These include the potential lack of dataset representativeness, insufficient analysis in comparing DNN and DNN+RF models, computational resource requirements, and the need for further exploration of real-time dataset challenges.

#### **Paper 2 : Automated Techniques for the Interpretation of Fetal Abnormalities.**

Literature Survey:

This review briefly discusses the use of ultrasound image segmentation techniques for assessing fetal biometric parameters, nuchal translucency, and the potential benefits for timely identification of fetal abnormalities, aiding high-risk pregnancies through continuous monitoring and parameter-based diagnostics.

Limitations:

The process of multistage decision and the data input is in binary form. The masks used by different operators act as a high-pass filter, which tend to amplify the noise. The fuzzy system is based on a series of If-Then rules, making the system complicated.

#### **Paper 3 : Early Diagnosis and Classification of Fetal Health Status from a Fetal Cardiotocography Dataset Using Ensemble Learning**

Literature Survey :

This study addresses the pressing issue of perinatal mortality, proposing an ensemble learning-based approach to classify fetal health using nonstress test (NST) data. With 6.3 million intrauterine fetal deaths reported annually by the World Health Organization (WHO), early diagnosis through NST is crucial. By leveraging a cardiotocography dataset, the study achieves over 99.5% accuracy in classifying fetal health, highlighting the potential of machine learning in improving perinatal care.

Limitations :

One limitation is the unbalanced nature of the dataset, which may affect model performance, especially in handling the smaller pathological class. Further studies are needed to explore strategies for addressing this imbalance and improving model robustness.

#### **Paper 4 : Ultrasound Diagnosis of Fetal Anomalies**

Literature Survey:

The primary objectives of this review are to evaluate the diagnostic accuracy of fetal anomaly screening in low-risk pregnant women during both the first and second trimesters, comparing single- and two-stage screening approaches. The secondary objective is to investigate factors, including clinical and methodological variables, that may contribute to heterogeneity in screening performance among studies.

Limitations:

The limitations of this paper may include the potential for selection bias if the study primarily focuses on specific patient populations, thus limiting the generalizability of findings to a broader demographic. Additionally, the paper's accuracy might be influenced by the proficiency of the sonographers and the quality of ultrasound equipment used, which can vary across different healthcare settings and regions, affecting the overall reliability of the ultrasound diagnosis.

#### **Paper 5: Detecting and Classifying Fetal Brain Abnormalities using Machine Learning Techniques**

Literature Survey:

Studies involve the application of machine learning algorithms to various medical imaging modalities, such as MRI or ultrasound, to detect and classify fetal brain abnormalities. They often explore feature extraction, segmentation, and classification methods, aiming to improve early diagnosis and intervention in cases of brain-related anomalies during pregnancy. Researchers may use neural networks, support vector machines, or other machine learning approaches to achieve accurate and automated detection and classification. It is important to consult specific papers in the field to gain more detailed insights.

Limitations:

The limitations of this paper may include the need for large and diverse datasets, as fetal brain abnormalities are relatively rare, which could impact the model's generalizability. Additionally, the accuracy of classification may be influenced by the quality of imaging data, and interpretability of the machine learning model's decision-making process may remain a challenge, hindering clinical adoption.

### **Mini Project Contribution:**

- **Research Papers for Literature Survey** -Nishika,Gouresh,Vaishnavi
- **Research for framework & code**- Vivek
- **Additional information research**- Aryan Surve
- **DataSet Research**- Gouresh,Nishika,Vaishnavi,Aryan
- **Code**-Vivek,Vaishnavi,Gouresh,Aryan,Nishika
- **Log Book** -Vaishnavi
- **Report**-Aryan,Nishika,Vaishnavi,Gouresh
- **Powerpoint Presentation**- Gouresh,Aryan,Nishika

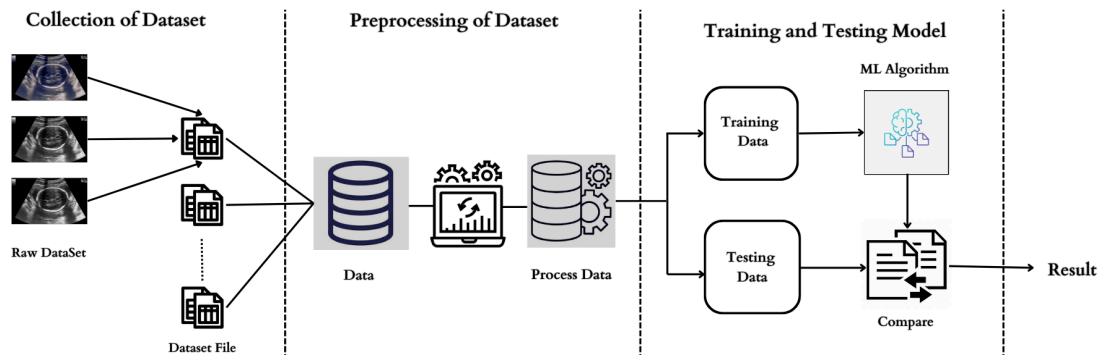
## CHAPTER 3

### PROPOSED SYSTEM

#### 3.1 Introduction:

- **Develop a Machine Learning Model:** Create a machine learning model using CNN (Convolutional Neural Network) capable of detecting fetal abnormalities from medical ultrasound images.
- **Data Collection and Preprocessing:** Gather a comprehensive dataset of ultrasound images of the brain of fetus. Preprocessing system and augment the data to ensure the model's robustness.
- **Real-time Detection:** Implement the model to perform real-time or near-real-time fetus abnormality detection for potential clinical use, if applicable.
- **Documentation and Codebase:** Maintain clear and comprehensive documentation for the project, including code, data annotations, model architecture, and experimental results, to facilitate reproducibility and further research.

#### 3.2 Architecture/ Framework:



##### 1. Image preprocessing and model training:

- In this part, images are loaded, preprocessed, and used to train a convolutional neural network (CNN) model for binary classification (healthy vs. unhealthy).
- The preprocessing steps include histogram equalization, median blur, thresholding, contour detection, cropping, and resizing.
- The CNN model architecture consists of multiple convolutional layers followed by max-pooling layers and fully connected layers.
- Data augmentation techniques such as rotation, shifting, shearing, zooming, and flipping are applied using the 'ImageDataGenerator' class.
- The model is compiled with binary cross-entropy loss and Adam optimizer.
- Training and validation are performed using 'model.fit()' with the training and testing data generators.
- Evaluation of the model is done using 'model.evaluate()'.

## 2. Flask web application:

- This part creates a simple Flask web application for uploading images and making predictions using the trained model.
- Flask routes are defined for rendering the index page and handling file uploads.
- Uploaded images are saved to a specified folder ('uploads') and then loaded for prediction.
- The trained model is loaded using 'load\_model()' from TensorFlow.
- Preprocessing steps are applied to the uploaded image before making predictions.
- Predictions are made using the loaded model, and the result is printed indicating whether the uploaded image is classified as healthy or unhealthy.
- The uploaded image is removed from the server after prediction.

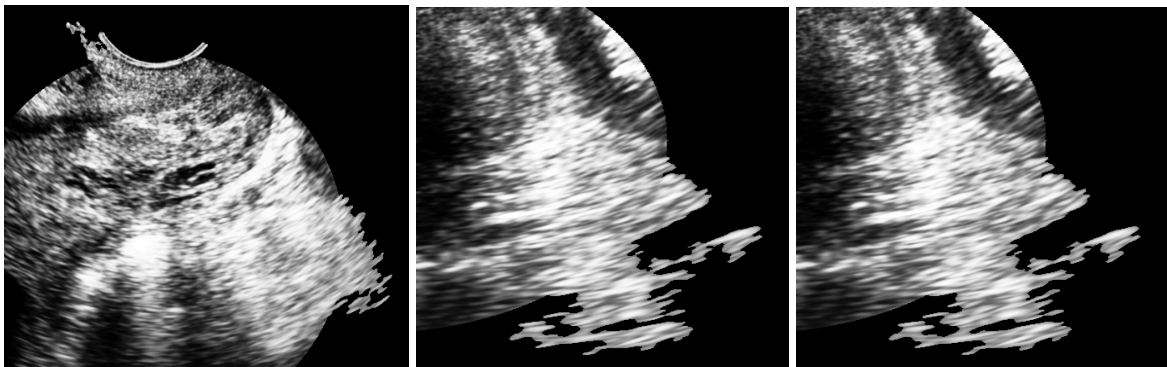
### Architecture and frameworks used:

- The image preprocessing and model training part primarily utilize the OpenCV library ('cv2') for image processing tasks and TensorFlow ('tensorflow.keras') for building and training the CNN model.
- Data augmentation is performed using the 'ImageDataGenerator' class from TensorFlow.
- The Flask web application part utilizes the Flask framework for building web applications and handling HTTP requests.
- The provided code combines the functionalities of image processing, deep learning model training, and web application development using Python libraries such as OpenCV, TensorFlow, and Flask.

## 3.3 Algorithm and Process Design:

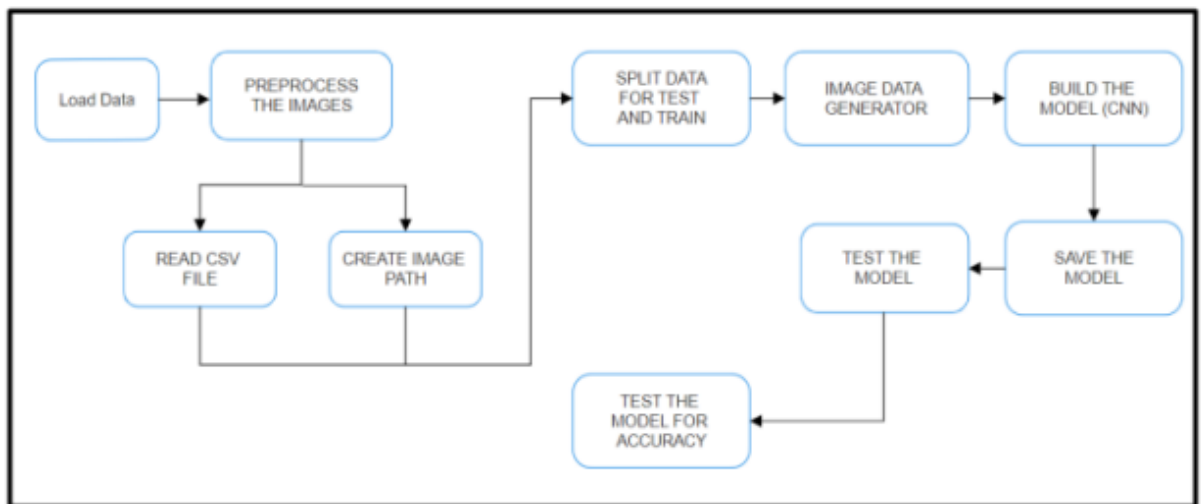
- Data Preparation:
  - Load and prepare the fetal health dataset, including checking for duplicates and splitting it into features (X) and the target variable (y).
- Data Preprocessing:
  - Standardize the feature data using StandardScaler.

### IMAGES AFTER PRE PROCESSING:



- **Model Training and Evaluation:**
  - Train and evaluate multiple classifiers (SVC, K-Nearest Neighbors, AdaBoost, Gradient Boosting, and Random Forest) for fetal health classification.
  - Assess the performance of each model using accuracy.

Block Diagram :



### 3.4 Details of Hardware & Software :

#### Hardware

- High performance computing resources(GPU)
- Storage for large datasets.

#### Software and Tools

- Python programming language
- Deep learning frameworks(TensorFlow)
- Data preprocessing libraries(cv2,os)
- Visualization tools(Matplotlib,Seab)
- Api(Flask)

### 3.5 Experiment and Results:

#### 1. Machine Learning Models Used:

- Convolutional Neural Network (CNN)

#### 2. Model Training and Evaluation:

- Training the model on the training set.
- Making predictions on the testing set.
- Calculating test accuracy and train accuracy to check whether the model is overtrained

or not

- Calculating accuracy using `accuracy\_score`.
- Presenting the confusion matrix for some models using `confusion\_matrix`.
- Including the accuracy and confusion matrix for each model.

### 3. Results:

#### Convolutional Neural Network(CNN):

```
PART 1 DONE
PART 2 DONE
PART 3 DONE
PART 4 DONE
Found 8596 validated image filenames belonging to 2 classes.
c:\Users\Vivek\AppData\Local\Programs\Python\Python311\Lib\site-packages\keras\src\preprocessing\image.py:1137: UserWarning: Found 1324 invalid image
  warnings.warn(
Found 2126 validated image filenames belonging to 2 classes.
c:\Users\Vivek\AppData\Local\Programs\Python\Python311\Lib\site-packages\keras\src\preprocessing\image.py:1137: UserWarning: Found 354 invalid image
  warnings.warn(
PART 5 DONE
Epoch 1/5
269/269 [=====] - 299s 1s/step - loss: 0.7141 - accuracy: 0.5275 - val_loss: 0.6915 - val_accuracy: 0.5292
Epoch 2/5
269/269 [=====] - 286s 1s/step - loss: 0.6916 - accuracy: 0.5293 - val_loss: 0.6915 - val_accuracy: 0.5292
Epoch 3/5
269/269 [=====] - 283s 1s/step - loss: 0.6915 - accuracy: 0.5293 - val_loss: 0.6915 - val_accuracy: 0.5292
Epoch 4/5
269/269 [=====] - 284s 1s/step - loss: 0.6915 - accuracy: 0.5293 - val_loss: 0.6915 - val_accuracy: 0.5292
Epoch 5/5
269/269 [=====] - 281s 1s/step - loss: 0.6915 - accuracy: 0.5293 - val_loss: 0.6915 - val_accuracy: 0.5292
PART 6 DONE
67/67 [=====] - 29s 435ms/step - loss: 0.6915 - accuracy: 0.5292
Test Accuracy: 0.5291627645492554
269/269 [=====] - 116s 432ms/step - loss: 0.6915 - accuracy: 0.5293
Train Accuracy: 0.5293159484863281
```

#### Other Deeper Neural Networks of CNN:

```
PART 1 DONE
PART 2 DONE
PART 3 DONE
PART 4 DONE
Found 9920 validated image filenames belonging to 2 classes.
Found 2480 validated image filenames belonging to 2 classes.
PART 5 DONE
Epoch 1/10
310/310 [=====] - 199s 639ms/step - loss: 0.6616 - accuracy: 0.5742 - val_loss: 0.6541 - val_accuracy: 0.5802
Epoch 2/10
310/310 [=====] - 164s 530ms/step - loss: 0.6373 - accuracy: 0.5963 - val_loss: 0.6440 - val_accuracy: 0.6024
Epoch 3/10
310/310 [=====] - 161s 520ms/step - loss: 0.6294 - accuracy: 0.6076 - val_loss: 0.6283 - val_accuracy: 0.6073
Epoch 4/10
310/310 [=====] - 162s 524ms/step - loss: 0.6242 - accuracy: 0.6207 - val_loss: 0.6249 - val_accuracy: 0.6173
Epoch 5/10
310/310 [=====] - 162s 523ms/step - loss: 0.6152 - accuracy: 0.6262 - val_loss: 0.6197 - val_accuracy: 0.6117
Epoch 6/10
310/310 [=====] - 161s 519ms/step - loss: 0.6107 - accuracy: 0.6342 - val_loss: 0.6124 - val_accuracy: 0.6319
Epoch 7/10
310/310 [=====] - 162s 523ms/step - loss: 0.6016 - accuracy: 0.6428 - val_loss: 0.6048 - val_accuracy: 0.6306
Epoch 8/10
310/310 [=====] - 163s 525ms/step - loss: 0.5961 - accuracy: 0.6446 - val_loss: 0.6067 - val_accuracy: 0.6310
Epoch 9/10
310/310 [=====] - 164s 529ms/step - loss: 0.5878 - accuracy: 0.6552 - val_loss: 0.5981 - val_accuracy: 0.6274
...
310/310 [=====] - 169s 546ms/step - loss: 0.5814 - accuracy: 0.6633 - val_loss: 0.5864 - val_accuracy: 0.6536
PART 6 DONE
78/78 [=====] - 24s 305ms/step - loss: 0.5905 - accuracy: 0.6524
Test Accuracy: 0.6524193286895752
```



```

PART 1 DONE
PART 2 DONE
PART 3 DONE
PART 4 DONE
Found 9920 validated image filenames belonging to 2 classes.
Found 2480 validated image filenames belonging to 2 classes.
PART 5 DONE
Epoch 1/5
310/310 [=====] - 339s 1s/step - loss: 0.5681 - accuracy: 0.6786 - val_loss: 0.5156 - val_accuracy: 0.7020
Epoch 2/5
310/310 [=====] - 351s 1s/step - loss: 0.4787 - accuracy: 0.7433 - val_loss: 0.4800 - val_accuracy: 0.7423
Epoch 3/5
310/310 [=====] - 298s 961ms/step - loss: 0.4053 - accuracy: 0.8016 - val_loss: 0.4894 - val_accuracy: 0.7504
Epoch 4/5
310/310 [=====] - 297s 959ms/step - loss: 0.2935 - accuracy: 0.8679 - val_loss: 0.5442 - val_accuracy: 0.7544
Epoch 5/5
310/310 [=====] - 296s 955ms/step - loss: 0.1509 - accuracy: 0.9393 - val_loss: 0.7346 - val_accuracy: 0.7742
PART 6 DONE
78/78 [=====] - 27s 350ms/step - loss: 0.7346 - accuracy: 0.7742
Test Accuracy: 0.774193525314331

```

### 3.6 Conclusion and Future work:

- Exploring alternative models of transformer-based architectures which can potentially improve accuracy by capturing sequential or contextual information better than CNNs.
- Additional preprocessing techniques such as data augmentation, normalization, or feature scaling can enhance performance by improving the quality and consistency of input data for the model.
- Designing a user-friendly platform with seamless integration and intuitive interface ensures doctors can effortlessly access their reports after accurate data entry, fostering efficient communication and decision-making in healthcare settings.
- The future of Machine Learning in the Biomedical field is bright and promising, and yet much remains to be done.

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