A

Mini Project Report

On

HealthScan AI: An Intelligent Health Insight using CNN

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Third Year Engineering – Computer Science Engineering (Data Science)

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ABSTRACT

Automated analytical systems have begun to emerge as a database system that enables the scanning of medical images to be performed on computers and the construction of big data. Deep-learning artificial intelligence (AI) architectures have been developed and applied to medical images, making high-precision diagnosis possible. For diagnosis, the medical images need to be labeled and standardized. After pre-processing the data and entering them into the deep-learning architecture, the final diagnosis results can be obtained quickly and accurately. To solve the problem of overfitting because of an insufficient amount of labeled data, data augmentation is performed through rotation, using left and right flips to artificially increase the amount of data. Because various deep learning architectures have been developed and publicized over the past few years, the results of the diagnosis can be obtained by entering a medical image. Classification and regression are performed by a supervised machine-learning method and clustering and generation are performed by an unsupervised machine-learning method. When the convolutional neural network method is applied to the deep-learning layer, feature extraction can be used to classify diseases very efficiently and thus to diagnose various diseases.

CHAPTER 1

Introduction

The brain is the most important organ in the human body which controls the entire functionality of other organs and helps in decision making. It is primarily the control center of the central nervous system and is responsible for performing the daily voluntary and involuntary activities in the human body. The tumor is a fibrous mesh of unwanted tissue growth inside our brain that proliferates in an unconstrained way. This year at the age of 15 about 3,540 children were diagnosed with a brain tumor. The right way of understanding of brain tumor and its stages is an important task to prevent and to carry out the steps in curing the illness. To do so, magnetic resonance imaging (MRI) is widely used by radiologists to analyze brain tumors. The result of the analysis carried out in this paper reveals whether the brain is normal one or diseased one by applying deep learning techniques. In this paper and CNN are used in the classification of normal and tumor brain. It works like a human brain nervous system; on this basis a digital computer relates to large number of interconnections and networking which makes neural network to train with the use of simple processing units applied on the training set and stores the experiential knowledge. It has different layers of neurons which are connected. The neural network can acquire knowledge by using data set applied on learning process. There will be one input and output layer whereas there may be any number of hidden layers. In the learning process, the weight and bias are added to neurons of each layer depending upon the input features and on the previous layers (for hidden layers and output layers). A model is trained based on the activation function applied on the input features and on the hidden layers where more learning happens to achieve the expected output.

In the era of artificial intelligence (AI), the intersection of healthcare and technology has paved the way for innovative solutions to improve diagnostics and patient care. This project focuses on leveraging AI to enhance the detection and diagnosis of three significant medical conditions: skin diseases, pneumonia, and diabetic retinopathy. By harnessing the power of AI algorithms and analyzing medical imaging data from X-ray and CT scans, this project aims to revolutionize healthcare by providing accurate and efficient diagnostic tools. Skin diseases encompass a wide range of conditions, from common dermatitis to potentially life-threatening melanoma. Traditional methods of diagnosis often rely on visual inspection by dermatologists, which can be subjective and time-consuming. By utilizing AI algorithms trained on diverse datasets of dermatological images, this project aims to develop a robust system capable of accurately identifying various skin diseases. This AI-based approach promises faster diagnosis, early detection of abnormalities, and improved patient outcomes. Pneumonia is a leading cause of morbidity and mortality worldwide, particularly in vulnerable populations such as children and the elderly. X-ray imaging plays a crucial role in diagnosing pneumonia by revealing characteristic infiltrations in the lungs. However, interpreting X-ray images requires expertise and can be prone to human error. By employing AI algorithms trained on annotated X-ray datasets, this project seeks to automate pneumonia detection, enabling rapid and accurate diagnosis. By facilitating early detection and intervention, this AI-powered system has the potential to save lives and reduce healthcare costs. Diabetic retinopathy is a serious complication of diabetes mellitus and a leading cause of blindness globally. Early detection and timely intervention are critical to preventing vision loss. X-ray and CT scans can provide detailed images of the eye's internal structures, facilitating the detection of diabetic retinopathy-related abnormalities such as microaneurysms, hemorrhages, and exudates. By applying AI algorithms to analyze retinal images obtained from X-ray and CT scans, this project aims to develop a reliable system for diabetic retinopathy screening and diagnosis. This AI-based approach offers the potential to improve access to eye care services, particularly in underserved communities, and reduce the burden on healthcare providers.

1.1 Purpose

Brain tumors are a significant health concern, and early detection can significantly improve patient outcomes. The project can contribute to advancements in healthcare by developing a tool that aids in the early detection of brain tumors, potentially saving lives and improving the quality of life for affected individuals. Brain tumor detection projects can provide valuable data for medical research. The data collected and analyzed during the project can be used to better understand the characteristics of brain tumors, their prevalence, and potential trends or patterns in their occurrence. Developing a brain tumor detection system often involves the use of cutting-edge technologies, such as machine learning, computer vision, and medical imaging. These projects can drive technological innovation and potentially lead to the development of more accurate and efficient diagnostic tools. AI-based systems have the potential to enhance the accuracy and efficiency of diagnostic processes. By leveraging machine learning algorithms trained on vast amounts of data, these systems can identify patterns and abnormalities in medical images with a level of precision that surpasses human capabilities. This can lead to more reliable diagnoses and streamline the diagnostic workflow, saving time and resources for healthcare professionals. AI-powered diagnostic tools can help bridge gaps in access to healthcare services, particularly in underserved or remote areas where specialist expertise may be limited. By providing automated screening and diagnosis, these systems can extend the reach of healthcare services, enabling more people to receive timely and accurate medical assessments.

1.2 Objectives

Create a machine learning model that can accurately detect brain tumors in medical images, such as MRI or CT scans. Improve the accuracy of brain tumor detection compared to existing methods or baseline models. Aim to detect brain tumors at an earlier stage, increasing the chances of successful treatment and better patient outcomes. Develop an automated system that can analyze medical images and provide rapid and consistent results, reducing the reliance on manual interpretation. Minimize the number of false-positive results to prevent unnecessary patient anxiety and follow-up procedures. Enhance the speed of the detection process to ensure timely diagnosis and intervention. Enable early detection of skin diseases, pneumonia, and diabetic retinopathy through AI-based systems. Early detection allows for timely intervention and treatment, which can significantly improve patient outcomes and potentially prevent disease progression and complications. Facilitate broader access to healthcare services by developing AI-based diagnostic tools that can be deployed remotely or in resource-limited settings. These tools can help address disparities in healthcare access and improve equity in healthcare delivery by extending diagnostic capabilities to underserved populations.

1.3 Scope

Collect and preprocess a diverse dataset of brain MRI images, including cases with and without tumors, to train and test the detection model. Develop a machine learning or deep learning model capable of accurately classifying brain MRI scans as tumor or non-tumor cases. Create a user-friendly interface for uploading medical images and obtaining detection results. Implement validation and testing procedures, collaborating with healthcare professionals to ensure the system's reliability and accuracy. Address ethical considerations, including patient consent and data privacy, in the development and deployment of the system. Gathering diverse and representative datasets of medical images related to skin diseases, pneumonia, and diabetic retinopathy. This includes obtaining X-ray and CT scans of patients with relevant conditions and ensuring proper annotation of images by medical professionals for training AI algorithms. Designing and implementing AI algorithms, such as convolutional neural networks (CNNs) or deep learning architectures, tailored to each medical condition. Training these algorithms using annotated datasets to learn patterns indicative of skin diseases, pneumonia, and diabetic retinopathy in X-ray and CT scans. Preprocessing medical images to enhance quality, remove noise, and standardize formats. Extracting relevant features from images, such as lesion characteristics in skin diseases, pulmonary opacities in pneumonia, and retinal abnormalities in diabetic retinopathy, to facilitate AI-based analysis.

CHAPTER 2

Literature Review

The paper starts by highlighting the significance of medical imaging in disease diagnosis and treatment. It emphasizes that CNN-based models have shown notable improvements in tasks like image analysis and classification, making them particularly valuable in medical imaging applications. Advantages of CNNs in Medical Imaging The paper outlines various advantages of using CNNs in medical imaging, such as enhanced accuracy, reduced time and resource requirements, and the ability to handle class imbalances in datasets. These advantages make CNNs particularly suitable for medical image analysis tasks. Transfer Learning with Pre-trained CNNs The paper discusses the use of pre-trained CNN models and transfer learning techniques, which have shown promise in addressing challenges related to small datasets and limited computational resources. Transfer learning allows leveraging knowledge from models trained on large datasets to improve performance on medical imaging tasks. Challenges and Limitations Despite the advantages, the paper acknowledges several challenges and limitations associated with CNNs in medical imaging. These include the need for large and diverse datasets for training, as well as the limited interpretability of deep learning models, which can be critical in medical settings where decision-making transparency is essential. Research Directions and Opportunities Finally, the paper presents current and future research directions in the field, including the development of specialized CNN architectures tailored to medical imaging tasks and the exploration of new modalities and applications. This section highlights the potential for further advancements in medical imaging through the continued use and refinement of CNN techniques. Applications of CNNs in Disease Diagnosis: The paper also briefly mentions specific diseases for which CNN techniques have been applied successfully in medical image analysis, such as breast cancer, Alzheimer's disease, and brain tumors. This underscores the versatility and effectiveness of CNNs across a range of medical conditions. Overall, the paper provides a comprehensive overview of the application of CNNs in medical imaging, highlighting their benefits, challenges, and future research directions in this important area of healthcare technology.

Authors	**year**	**Imaging modality**	**Classification Target**	**Precision/ Accuracy**	**Models/Techniques**

Salehi, A.W.; Khan, s.; Gupta	2023	Ultrasound, X-ray, CT	Normal control(nc) and Pneumonia	Ultrasound: 100% precision; X-ray and CT: 93%	Pre-trained VGG-19 performed best on ultrasound images, demonstrating effectiveness on noisy data
Sarvamangala DR, Kulkarni RV.	2021	CT	Lung Nodule Detection	97.17% Accuracy	used gradient class activation for visualizing internal CT structure; Outperformed alexnet 2D-CNN and alexnet 3D-CNN
Yadav, S.S., Jadhav, S.M.	2019	Lung Image Patches	Interstitial Lung Disease (ILD)	95% Accuracy	Compared results with LBP, SIFT, and unsupervised RBM feature extraction methods
Abdar M, Yen N, Hung J	2018	MRI, Diffusion-Tensor Imaging (DIO)	Alzheimer's Disease (AD)	96.7% Accuracy	Used a six-layered CNN with data fusion model; Emphasized ROI size's minimal impact on classification.

CHAPTER 3

Proposed system

Brain tumors are a critical health concern, and their early detection is crucial for timely intervention and improved patient outcomes. This proposal outlines the development of an advanced Brain Tumor Detection System that leverages cutting-edge technology, including artificial intelligence (AI) and machine learning (ML), to enhance the accuracy and efficiency of brain tumor diagnosis. The BrainScan AI aims to automate the detection process, reduce the reliance on manual interpretation, and provide healthcare professionals with a reliable and rapid tool for brain tumor detection and characterization. Provide healthcare professionals with decision support tools that augment their expertise and improve clinical decision-making. AI-based systems can assist clinicians in interpreting medical images, identifying abnormalities, and generating differential diagnoses, enabling more informed treatment decisions and personalized patient care.

3.1 Features and Functionalities

- The system will be capable of ingesting MRI scans from various sources, including healthcare institutions, research databases, and digital archives. Data preprocessing techniques will be applied to standardize image formats and ensure data quality.
- The BrainScan AI will feature a user-friendly web-based interface that enables healthcare professionals to upload medical images easily. The interface will provide seamless interaction, allowing users to submit images, initiate analysis, and view results.
- The detection engine is responsible for processing uploaded MRI scans through the trained ML model. It will generate comprehensive reports detailing the presence, location, size, and characteristics of any detected brain tumors.
- Users, typically healthcare professionals, can easily upload brain MRI scans through the user interface. The system will support various image formats, ensuring compatibility with different acquisition devices.
- The system will provide real-time results, displaying the presence or absence of brain tumors on the uploaded image. Detected tumors will be outlined, and their characteristics, such as size and location, will be highlighted.
- Preprocessing of medical images to enhance quality, remove noise, and standardize formats, ensuring consistency across datasets.
- Extracting relevant features from medical images, such as lesion characteristics in skin diseases, pulmonary opacities in pneumonia, and retinal abnormalities in diabetic retinopathy, to facilitate AI-based analysis.
- Designing and implementing AI algorithms, including convolutional neural networks (CNNs) or deep learning architectures, tailored to each medical condition for accurate detection and classification.
- Training AI models using annotated datasets of medical images labeled with ground truth diagnoses, enabling the models to learn patterns indicative of skin diseases, pneumonia, and diabetic retinopathy.

- Validating the performance of AI models using metrics such as accuracy, sensitivity, specificity, and area under the receiver operating characteristic (ROC) curve, ensuring robustness and reliability in real-world settings.
- Integrating AI-based diagnostic tools into existing clinical workflows, such as electronic health record systems and radiology reporting platforms, to facilitate seamless interaction and incorporation into patient care processes.
- Developing user-friendly interfaces for healthcare professionals to interact with AI models, upload medical images, view diagnostic results, and interpret findings during patient consultations.
- Incorporating mechanisms for continuous model refinement and improvement based on feedback from clinical users and real-world performance data, ensuring adaptation to evolving healthcare needs and advancements in medical knowledge.

CHAPTER 4

Requirement Analysis

The Software Requirements Specification is produced at the culmination of the analysis task. The function and performance allocated to software as part of system engineering are refined by establishing a complete information description, a detailed functional and behavioral description, an indication of performance requirements and design constraints, appropriate validation criteria, and other data pertinent to requirements.

Operating System	Windows11
Coding Language	Python
Tool	Flutter 3.3.1 (GUI),Google Colab notebook
Front End	Flutter 3.3.1 (GUI), Python3.11
Backend	Tensor Flow hub 0.14. 0 Tensor flow 2.13.0 Fire Base 13.1.0 (Database)
Algorithm used	Convolution Neural Network [Image Classification using Supervised Learning]

Flutter 3.3.1 : Flutter allows developers to build cross-platform applications with a single codebase, which can save a significant amount of time and resources compared to building separate native apps for each platform. Flutter's hot reload feature enables developers to quickly and easily experiment with UI changes and see the results in real-time, which can greatly improve the development workflow. Flutter is an open-source UI software development kit created by Google for building natively compiled applications for mobile, web, and desktop from a single codebase. It uses the Dart programming language and provides a rich set of pre-designed widgets and tools for building beautiful and responsive user interfaces.

Tensor Flow 2.13.0 : TensorFlow is an open-source library for developing and deploying machine learning applications. It provides a flexible architecture for defining machine learning algorithms as dataflow graphs, where nodes represent mathematical operations and edges represent multidimensional data arrays (tensors) that flow between them. TensorFlow can be used to build and train models for various tasks, including natural language processing, image recognition, and handwriting recognition. It supports execution on CPUs, GPUs, and TPUs across various platforms, making it a popular choice for data scientists, software developers, and educators. TensorFlow also includes TensorBoard, a tool for visualizing the training process, underlying computational graphs, and metrics.

Tensor Flow hub 0.14. 0 : TensorFlow Hub is a library and repository for reusable machine learning models. It provides pre-trained models for tasks such as text embeddings, image classification, and more. The tensorflow_hub library allows you to easily download and use these models in your TensorFlow program with minimal code. TensorFlow Hub is open to community contributors and licensed under the Apache 2.0 License. Version 0.14.0 was released on July 13, 2023.

Convolution Neural Network [Image Classification using Supervised Learning] : CNNs are a type of neural network that is particularly well-suited for image classification tasks. They work by applying a series of convolutional filters to the input image, which help to identify patterns and features in the image. These filters are learned during training and can be thought of as "learning" to recognize specific features such as edges, shapes, or textures. After the convolutional layers, the CNN typically includes one or more fully connected layers, which are used to classify the image based on the features that have been extracted. During training, the weights of the convolutional filters and fully connected layers are adjusted to minimize the difference between the predicted class labels and the true class labels.

CHAPTER 5

Project Design

Fig 5.1(A) Patient's Dashboard

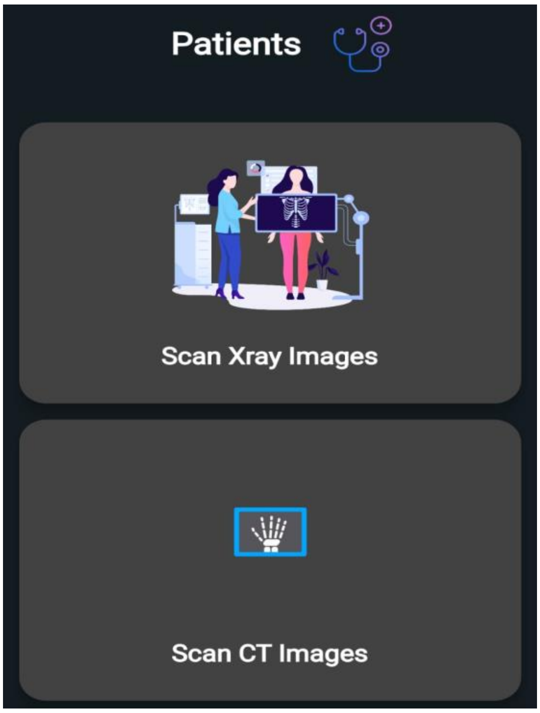

Fig 5.1(B) Patient's Dashboard

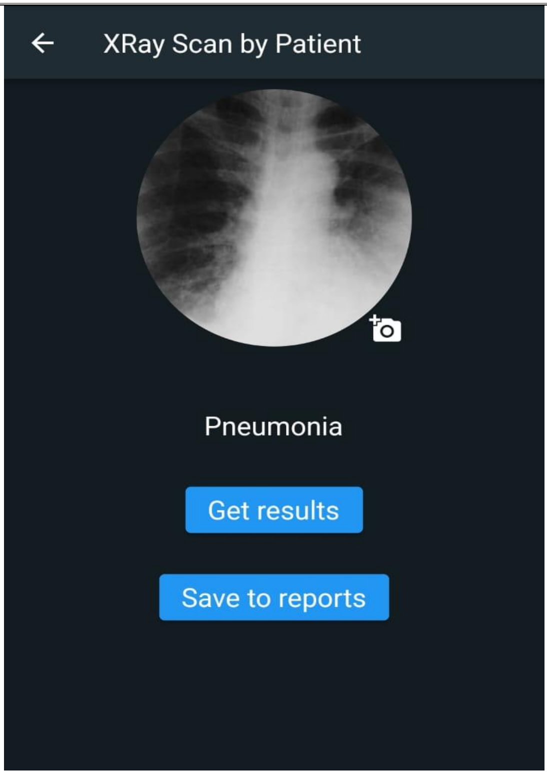

Fig 5.2 Pneumonia Detection

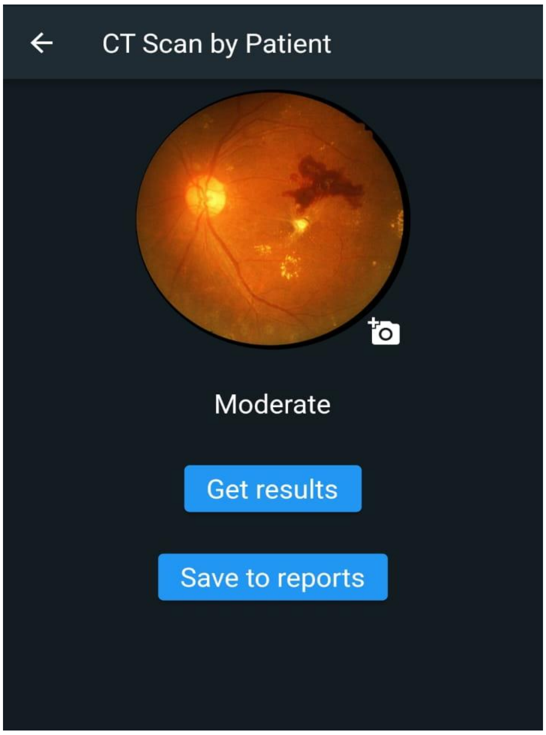

Fig 5.3 Diabetic retinopathy Level

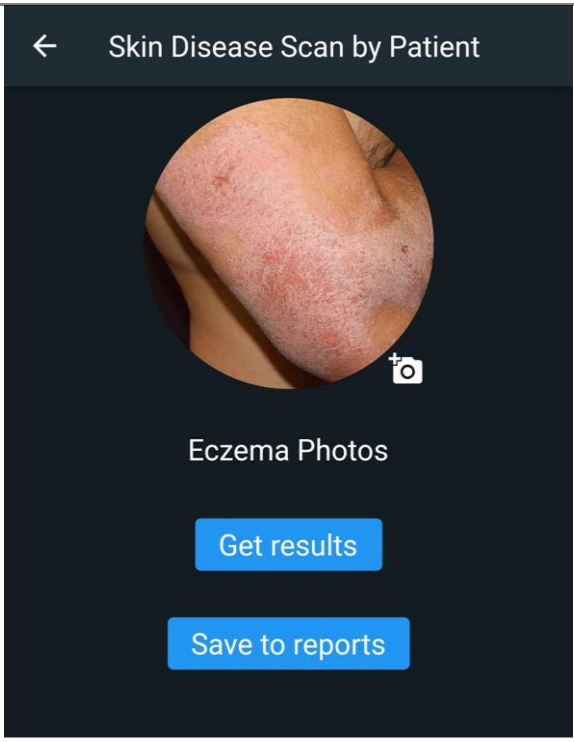

Fig 5.4 Skin Disease Detection

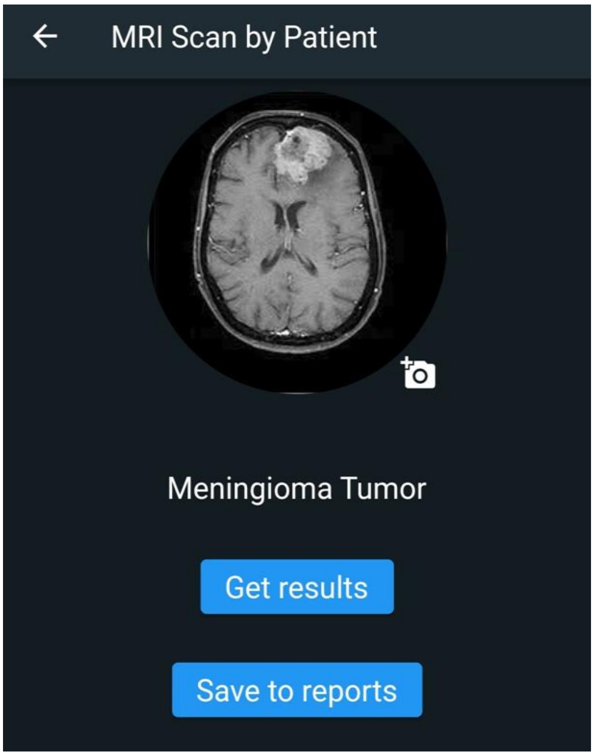

Fig 5.5 Tumor Detection

CHAPTER 6

Technical Specification

Data Collection: Collect a large and diverse dataset of CT scans, MRI scans, X-rays, and skin diseases images. The dataset should be labeled with the correct diagnosis or classification for each image.

Data Preprocessing: Preprocess the images to ensure that they have a consistent size, shape, and format. This may involve resizing the images, normalizing the pixel values, and augmenting the dataset with rotations, translations, and other transformations.

Model Architecture: Design a CNN architecture that is optimized for image classification tasks. This may involve using multiple convolutional layers, pooling layers, and fully connected layers. The final layer should use a softmax activation function to output a probability distribution over the possible classes.

Training: Split the dataset into training, validation, and test sets. Train the CNN on the training set using a supervised learning algorithm such as stochastic gradient descent or Adam. Use the validation set to tune the hyperparameters and prevent overfitting.

Evaluation: Evaluate the performance of the CNN on the test set using metrics such as accuracy, precision, recall, and F1 score. Compare the results to the performance of other models or human experts.

Deployment: Deploy the trained CNN as a web application, mobile application, or embedded system. Implement a user interface that allows users to upload images and receive a diagnosis or classification.

Some specific technical details for this project include:

Using pre-trained CNN models such as VGG16, ResNet, or Inception as a starting point for the model architecture. Using techniques such as model compression or quantization to deploy the model on resource-constrained devices. Using transfer learning techniques to fine-tune the pre-trained models on the specific dataset. Implementing data augmentation techniques such as random cropping, flipping, and rotations to increase the size and diversity of the dataset. Using techniques such as dropout, batch normalization, and early stopping to prevent overfitting. Implementing techniques such as model ensembling or stacking to improve the performance of the model.

CHAPTER 7

Project Scheduling

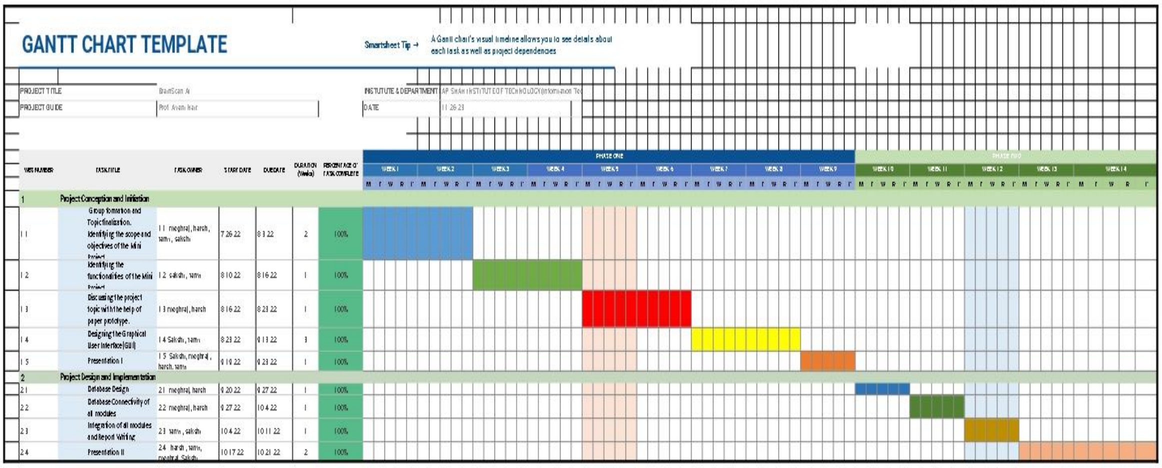

Fig 7.1 Gantt Chart

Here in the above figure, the rows of the chart contain the task titles such as the project conception and initialization as well as the project design and implementation which in subdivision contains the group formation, topic finalizing, prototype, GUI designing, backend implementation etc. The columns contain the duration of the task completed, the percentage of work completed, the number of weeks required to complete a particular task, the specific dates, and the team members who contributed towards the completion of tasks The detailed explanation of the Gantt chart is explained below: The project conception and initiation task were executed. The task of initiation included many more sub-tasks such as group formation and topic finalization which was performed during the 1 week of project initialization. The group formed included 4 members meghraj padwal, harsh mulik, tanvi mirgal and sakshi jamdhade, and the finalized topic was HealthScan AI: An Intelligent Health Insight using CNN. Further, the upcoming week led to the task of identifying the scope and objectives of the mini projects.The next sub-task was to identify the functionalities of the project, which was done by the two members sakshi jamdhade, and tanvi mirgal in a span of one week. The discussion of the project topic with the help of a paper prototype was completed by meghraj padwal, harsh mulik within one week from. The next main task of Graphical User Interface (GUI) designing was completed by sakshi jamdhade and tanvi mirgal within 2 weeks. The next week the members worked on the preparation of Presentation I. The next major task was database design and implementation. It took 5 weeks to complete the final implementation. The database Design and connectivity of all modules were done by meghraj padwal and harsh mulik during the course time of 2 weeks. The integration of all modules and report writing was completed by sakshi jamdhade and tanvi mirgal members. The preparation of final presentation II work was equally shared by all the group members in the time of 2 weeks.

CHAPTER 8

Result

Improved Diagnostic Accuracy: AI algorithms can enhance diagnostic accuracy by accurately identifying and classifying skin diseases, pneumonia, and diabetic retinopathy from medical imaging data. This can lead to more reliable diagnoses, reduced errors, and better patient management.

Early Detection and Intervention: AI-based systems enable early detection of medical conditions, such as skin diseases, pneumonia, and diabetic retinopathy, facilitating timely intervention and treatment. Early detection can prevent disease progression, reduce complications, and improve patient outcomes.

Streamlined Diagnostic Workflow: Integration of AI-based diagnostic tools into clinical workflows can streamline the diagnostic process, saving time and resources for healthcare professionals. Automated analysis of medical images accelerates diagnosis, enabling prompt treatment decisions and improved patient throughput.

Enhanced Access to Healthcare Services: AI projects can extend access to healthcare services by providing diagnostic support in remote or underserved areas. Telemedicine platforms equipped with AI-based diagnostic tools enable remote consultations and diagnostic assessments, improving access to specialized care.

Reduced Healthcare Costs: Early detection and accurate diagnosis facilitated by AI technologies can lead to cost savings for healthcare systems. By preventing disease progression, reducing hospitalizations, and optimizing resource utilization, AI projects contribute to healthcare cost containment and efficiency.

Improved Patient Outcomes: Timely diagnosis and intervention enabled by AI-driven diagnostics improve patient outcomes and quality of life. Early detection of skin diseases, pneumonia, and diabetic retinopathy allows for prompt treatment initiation, preventing complications and minimizing disease-related morbidity and mortality.

Advancements in Medical Research: AI projects generate valuable insights and data that contribute to advancements in medical research and knowledge. Analysis of large-scale medical imaging datasets enhances understanding of disease mechanisms, risk factors, and treatment responses, fostering innovation in clinical practice and therapeutic strategies.

Empowerment of Healthcare Professionals: AI-based diagnostic tools empower healthcare professionals by augmenting their expertise and decision-making capabilities. Interpretation of medical images assisted by AI algorithms enhances diagnostic confidence, enabling clinicians to make informed treatment decisions and provide personalized patient care.

Enhanced Patient Engagement and Education: AI projects facilitate patient engagement and education by providing accessible diagnostic information and resources. Patient-facing interfaces equipped with AI-driven diagnostics empower individuals to understand their health conditions, adhere to treatment plans, and actively participate in their healthcare management.

CHAPTER 9

Conclusion

In summary, the development of a HealthScan AI represents a remarkable leap forward in the field of medical diagnostics. This project has aimed to address a pressing healthcare challenge by harnessing the power of cutting-edge technology, specifically machine learning and artificial intelligence (AI), to improve the early detection of brain tumours, Diabetic retinopathy detection using ct scans, pneumonia using X-ray scans, skin disease detection. Throughout the project's journey, we have meticulously defined the problem, established objectives, and meticulously outlined the system's architecture and functionalities. As proposed, it promises to revolutionize the process of identifying and characterizing brain tumours, skin diseases, pneumonia detection diabetic retinopathy offering numerous benefits to healthcare professionals, patients, and the broader medical community. The HealthScan AI represents a powerful marriage of technology and medicine, a testament human innovation and a dedication to enhancing patient care. By improving the early detection of brain tumours, skin diseases, pneumonia detection diabetic retinopathy this system stands poised to save lives, reduce the burden of disease, and advance the field of medical imaging and AI in healthcare. It is a testament to the transformative potential of technology to address some of the most pressing challenges in medicine and improve the well-being of individuals and communities around the world.

CHAPTER 10

Future Work

We can experiment with different deep learning architectures such as ResNet, Inception, and DenseNet to see if they perform better than the current architecture for brain tumor detection, pneumonia detection, diabetic retinopathy, and skin diseases detection. We can explore transfer learning techniques where a pre-trained model is fine-tuned on a smaller dataset for the specific task of brain tumor detection, pneumonia detection, diabetic retinopathy, and skin diseases detection. We can use data augmentation techniques such as rotation, flipping, and zooming to increase the size of the dataset and improve the model's performance. We can use ensemble learning techniques where multiple models are combined to improve the overall performance of the system. We can work on developing a real-time detection system where the model can detect brain tumors, pneumonia, diabetic retinopathy, and skin diseases in real-time using video or live camera feed. We can integrate the model with medical devices such as MRI machines, X-ray machines, and CT scans to automate the detection process and reduce the workload of medical professionals. We can work on making the model more explainable by visualizing the features learned by the model and providing insights into how the model is making its predictions. We can conduct clinical trials to evaluate the effectiveness of the model in a real-world setting and compare it with the performance of medical professionals.

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