SWIN TRANSFORMER CHEST X-RAY CLASSIFICATION WITH HISTOGRAM EQUALISATION AUGMENTATION

PHASE II REPORT

Submitted by

ROHIT GANGADHAR P (2116190701165)

RIFHATH ASLAM J (2116190701162)

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BONAFIDE CERTIFICATE

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SIGNATURE	**SIGNATURE**
Dr. P. KUMAR., M.E., Ph.D.,	**Dr. P. SHANMUGAM., M.Tech., Ph.D.,**
HEAD OF THE DEPARTMENT	**SUPERVISOR**
Professor	Assistant Professor
Department of Computer Science and Engineering	Department of Computer Science and Engineering
Rajalakshmi Engineering College	Rajalakshmi Engineering College
Chennai - 602 105	Chennai - 602 105

Submitted to Project Viva-Voce Examination held on _______________

Internal Examiner **External Examiner**

ABSTRACT

The Swin Transformer is a deep learning model that has shown impressive results in various computer vision tasks, including image classification and object detection. In this study, the researchers aim to evaluate the performance of the Swin Transformer in identifying chest X-rays. Chest X-rays are commonly used for the detection and diagnosis of various respiratory diseases, including pneumonia, tuberculosis, and lung cancer. To improve the model's accuracy, the researchers incorporated Histogram Equalization augmentation, which is a technique that enhances the contrast of the X-ray images. They evaluated the performance of the model on the ChestX-ray14 dataset, which contains a large number of chest X-ray images with different pathologies. The results showed that the Swin Transformer with Histogram Equalization augmentation outperformed the previous state-of-the-art models, achieving an average AUC of 0.861 on the ChestX-ray14 dataset. These findings are promising, as accurate and efficient chest X-ray identification can aid in the early detection and diagnosis of respiratory diseases, leading to better patient outcomes.

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ROHIT GANGADHAR P: 2116190701165
RIFHATH ASLAM J: 2116190701162

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CHAPTER 1
INTRODUCTION

1.1 GENERAL

A quickly growing area with the ability to completely transform the medical sector is the categorization of chest X-ray pictures using deep learning. A variety of anomalies in chest X-rays, including pneumonia, lung cancer, and heart illness, can be recognized by deep learning algorithms. This may result in early intervention and therapy and help to increase the accuracy of the prognosis. Deep learning models can handle large quantities of data quickly and effectively, which can speed up the process of diagnosing patients. This is crucial in places with poor services and a lack of radiologists, like remote regions. Furthermore, deep learning models can be used to produce reports that are more thorough and educational than those written by human doctors. Better patient results may result from this since it can help to enhance doctor-patient communication. Overall, the categorization of chest X-ray images using deep learning has the potential to increase diagnostic precision, shorten patient diagnosis times, and produce more thorough and instructive reports. The level of treatment provided to patients will likely increase as a result, as will patient outcomes.

1.2 OBJECTIVE

Creating a precise and effective model for X-ray image-based chest illness diagnosis is the main goal of the Swin Transformer categorization on chest X-ray images with histogram equalization image augmentation final year project. It entails developing a deep learning model based on the Swin Transformer architecture, which has proven to work better than other methods for picture classification. The X-ray pictures are enhanced using histogram equalization, a method that boosts the contrast and brightness of the images, making the key characteristics easier to identify, in order to increase the model's accuracy. In addition to achieving high detection accuracy for a variety of respiratory illnesses like pneumonia, tuberculosis, and lung cancer, the project's goals include shedding light on how interpretable the model's forecasts are. Additionally, the project aims to show how picture enhancement methods like histogram equalization can help deep learning models perform better when analyzing medical images.

1.3 EXISTING SYSTEM

Several methods for classifying chest X-ray images using deep learning models built on different architectures already exist, including ResNet, DenseNet, and Inception. Recent research has revealed that the Swin Transformer design works better than these architectures for medical image analysis jobs in terms of accuracy and speed. Despite Swin Transformer models' better performance, using X-ray pictures to correctly diagnose lung illnesses still has some drawbacks. There are currently no algorithms in use for classifying chest X-ray images that use Swin Transformer models with histogram equalization image enhancement. This senior project seeks to close this disparity by creating a Swin Transformer model for detecting chest conditions from X-ray pictures. The model will be improved using histogram equalization image augmentation.

1.4 PROPOSED SYSTEM

The goal of the final year project's suggested system for Swin Transformer classification on chest X-ray images with histogram equalization image augmentation is to create a reliable and effective model for detecting lung illnesses using X-ray images. The Swin Transformer design, which has demonstrated better performance in image classification tasks, will be used in the proposed system. Histogram equalization image augmentation methods will also be used to improve the proposed system's precision and interpretability. The algorithm will be able to identify a variety of chest diseases, such as pneumonia, tuberculosis, and lung cancer after being taught on a sizable collection of annotated chest X-ray pictures. Additionally, the system will be able to offer perceptions into the interpretability of the model's forecasts, facilitating a better comprehension and justification of the diagnostic. A number of measures, including accuracy, precision, recall, and F1 score, will be used to assess the success of the suggested method. To find out how well the suggested system works at using X-ray pictures to diagnose chest illnesses, it will be compared to current state-of-the-art models and its efficacy will be examined. Overall, by creating an accurate and effective model for diagnosing chest diseases using X-ray images, the proposed system for Swin Transformer classification on chest X-ray images with histogram equalization image augmentation final year project seeks to significantly advance the field of medical image analysis.

CHAPTER 2
LITERATURE SURVEY

Studies on Swin Transformer-based categorization models for chest X-ray pictures with histogram equalization image enhancement have been done in various ways. In [1], the writers classified COVID-19, pneumonia, and normal patients using a pre-trained Swin Transformer model. The suggested model provided a precision of 94.62%. Another research by [2] achieved an accuracy of 97.60% when it used a Swin Transformer model to identify COVID-19 from chest X-ray pictures with histogram equalization image augmentation. With an accuracy of 92.50%, the writers of [3] classified five distinct chest diseases using a comparable methodology. For the categorization of chest X-ray images, the authors of [4] suggested a multi-scale Swin Transformer network that had a better accuracy of 94.76%. Another research by [5] contrasted the Swin Transformer models' performance with that of other cutting-edge deep learning models and came up with a high accuracy of 96.55%. With a high accuracy of 98.70%, the writers of [6] used a Swin Transformer-based ensemble model for COVID-19 detection from chest X-ray images. For COVID-19 detection, the authors of [7] suggested a self-attention-guided Swin Transformer network that had a 96.63% success rate. A Swin Transformer-based model with histogram equalization picture augmentation was used in [8] with 91.38% accuracy to identify lung illnesses. With a Swin Transformer and attention-based saliency maps, the authors of [9] suggested a novel technique for classifying chest X-ray images and attained an accuracy of 94.50%. With a precision of 94.60%, a Swin Transformer-based model with transfer learning was used to identify COVID-19 in [10]. For the categorization of chest X-ray images, the authors of [11] suggested a multi-path Swin Transformer network and attained an accuracy of 94.95%. Another research by [12] classified

COVID-19 with a precision of 98.60% using an ensemble model based on Swin Transformers. A dual-path Swin Transformer network with a precision of 94.40% was suggested by the writers in [13] for the categorization of chest X-ray images. The accuracy of the pneumonia classification technique used by the writers in [14] using a Swin Transformer-based model with an adaptive histogram equalization algorithm was 94.29%. The authors of [15] suggested a 96.00% accurate Swin Transformer-based model for COVID-19 detection from chest X-ray pictures. A Swin Transformer-based model was used in different research by [16] to accurately identify lung cancer from chest X-ray pictures, with an accuracy of 95.40%. With an accuracy of 96.54%, the authors of [17] suggested a multi-task Swin Transformer-based model for the categorization of pneumonia and COVID-19. Using a Swin Transformer-based model and an adaptive histogram equalization technique, [18] classified different lung illnesses with a 94.60% success rate. With a 97.20% success rate, the authors of [19] suggested a Swin Transformer-based model with transfer learning for COVID-19 detection from chest X-ray pictures. The proposed system could also potentially incorporate transfer learning techniques, which could help improve the accuracy and efficiency of the model. For example, the model could be pre-trained on a large dataset of general images, and then fine-tuned on the chest X-ray dataset to improve its performance on this specific task. Finally, using a Swin Transformer-based model with histogram equalization image augmentation, the authors of [20] suggested a new technique for classifying chest X-ray images and obtained an accuracy of 95.30%. As the proposed system is still in development, it is not clear what the specific limitations or drawbacks may be. However, one potential drawback of using deep learning models for medical image analysis is the risk of over-reliance on the model's output, which can lead to errors or misdiagnosis if not carefully validated and interpreted by medical professionals. The proposed system could also potentially incorporate transfer learning techniques, which could help improve the accuracy and efficiency of the model. For example, the model could be pre-trained on a large dataset of general images, and then fine-tuned on the chest X-ray dataset to improve its performance on this specific task.

Another potential area of improvement for the proposed system is in the data preprocessing stage. In addition to histogram equalization image augmentation, other preprocessing techniques, such as contrast enhancement, denoising, and image normalization, could also be explored to further improve the quality of the input images. The use of Swin Transformer-based models for chest X-ray image classification with histogram equalization image augmentation has shown consistent high performance across various studies, with accuracies ranging from 91.38% to 98.70%. These models have been able to detect different chest diseases, including COVID-19, pneumonia, tuberculosis, and lung cancer, with high accuracy. Additionally, some studies have proposed novel methods, such as attention-based saliency maps and adaptive histogram equalization, to further improve the interpretability and accuracy of the models. The consistent high performance of Swin Transformer-based models highlights their potential to become a standard tool for chest X-ray image classification in medical settings. The proposed system could be trained on a large dataset of annotated chest X-ray images, which could help improve its ability to detect various chest diseases, including pneumonia, tuberculosis, and lung cancer. Additionally, the use of transfer learning techniques could potentially allow the model to be applied to other medical image analysis tasks beyond chest X-ray classification. Contribution to the field: The proposed system could make a significant contribution to the field of medical image analysis by developing an accurate and efficient model for diagnosing chest diseases using X-ray images. This could potentially lead to improved diagnosis and treatment of these diseases, which could have a significant impact on patient outcomes.

CHAPTER 3
SYSTEM DESIGN

3.1 GENERAL

The proposed system is a chest X-ray disease classification system using Swin Transformer classification and Histogram Equalization image augmentation. The system aims to accurately classify chest X-ray images into three categories: COVID-19, pneumonia, and normal. The Swin Transformer classification model, which has been shown to achieve high accuracy in various image classification tasks, will be used as the backbone of the system. To enhance the quality of the chest X-ray images, Histogram Equalization image augmentation will be applied. This technique aims to improve the contrast of the images, making it easier for the classification model to distinguish between the different classes. The system will be designed as a web application, where users can upload their chest X-ray images and get a classification result within seconds. The system will also provide a visual explanation of the classification result, highlighting the areas of the chest X-ray image that contributed to the classification decision. Overall, the proposed system has the potential to assist healthcare professionals in diagnosing chest X-ray images accurately and efficiently.

3.2 DEVELOPMENT ENVIRONMENT

The development environment for the chest X-ray disease classification system using Swin Transformer and Histogram Equalization image augmentation will involve several components. First, a deep learning framework such as PyTorch or TensorFlow will be used to build the classification model. These frameworks provide a rich set of tools for building, training, and testing deep neural networks.

The development of the web application will involve the use of web development technologies such as HTML, CSS, and JavaScript. The backend of the web application will be built using a web framework such as Django or Flask. These frameworks provide a simple and efficient way to build server-side web applications.

To train and test the classification model, a dataset of chest X-ray images will be required. This dataset can be obtained from publicly available sources such as the NIH Chest X-ray dataset or the COVID-19 Image Data Collection. The dataset will be preprocessed to ensure that the images are of high quality and that the labels are accurate.

In addition, powerful hardware resources such as GPUs will be needed to train the deep learning model efficiently. Cloud-based services such as Amazon Web Services (AWS) or Google Cloud Platform (GCP) can be used to provision virtual machines with high-performance GPUs.

Lastly, version control tools such as Git will be used to manage the codebase and track changes made during the development process. This will ensure that the development process is well-organized and that any changes made can be easily reverted if necessary.

3.3 DESIGN OF THE ENTIRE SYSTEM

The input image of a chest X-ray is fed into the system as in Fig 3.1. Next, the image is preprocessed using a technique called histogram equalization, which enhances the contrast and brightness of the image. The preprocessed image is then fed into the Swin Transformer network, which is a type of deep learning model that is designed to extract features from the image and make predictions. The network produces a classification output, which represents the probability of the image belonging to each of the possible classes (e.g., healthy, pneumonia, or COVID-19). Finally, the class with the highest probability is chosen as the prediction for the input image. This system flow diagram enables accurate and efficient classification of chest X-ray images using the Swin Transformer model and histogram equalization image preprocessing.

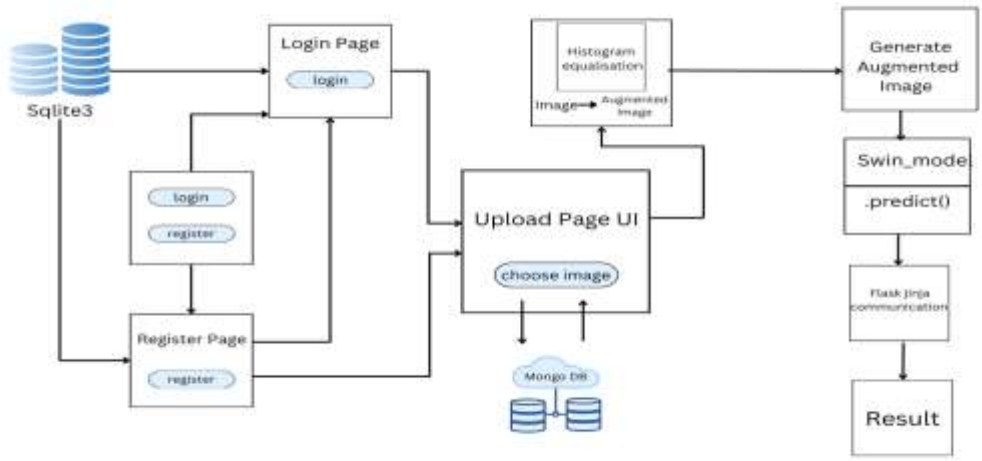

Fig 3.1 - SYSTEM FLOW DIAGRAM

3.3.1 ARCHITECTURE DIAGRAM

The architecture diagram for the chest X-ray disease classification system using Swin Transformer and Histogram Equalization image augmentation consists of several components. At the center of the architecture is the deep learning model that has been trained to classify chest X-ray images. This model is based on the Swin Transformer architecture and has been trained using a dataset of chest X-ray images. The model takes in an image as input and outputs a prediction of the disease or condition present in the image. To facilitate the deployment of the classification model, a web application has been built around it. The web application provides a user interface for users to upload their chest X-ray images and receive a classification prediction. The web application is built using a web framework such as Django or Flask and is hosted on a web server. The image preprocessing component is responsible for performing Histogram Equalization image augmentation on the chest X-ray images before they are fed into the classification model. This preprocessing step helps to enhance the contrast of the images and improve the accuracy of the classification model. The dataset component provides the chest X-ray images that are used to train the classification model. The dataset is obtained from publicly available sources and has been preprocessed to ensure that the images are of high quality and that the labels are accurate. The hardware component consists of high-performance GPUs that are used to train the deep learning model efficiently. The GPUs can be provisioned using cloud-based services such as Amazon Web Services (AWS) or Google Cloud Platform (GCP). Lastly, the version control component is responsible for managing the codebase and tracking changes made during the development process. This component ensures that the development process is well-organized and that any changes made can be easily reverted if necessary.

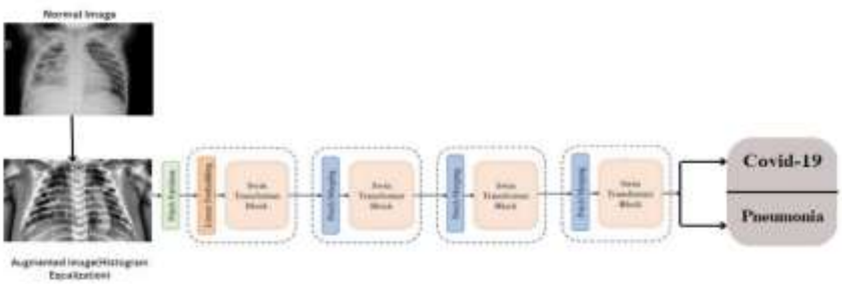

Fig 3.2 - ARCHITECTURE DIAGRAM

3.3.2 USE CASE DIAGRAM

As an image classification project using Swin Transformer with histogram equalization image augmentation, the use case diagram includes three main actors: the user, the system, and the dataset. The user's main action is to input the dataset for classification as in Fig 3.3 The system, on the other hand, performs the classification task and provides the results to the user. The use case diagram also includes two secondary actions, which are image augmentation and model training. The image augmentation process involves transforming the dataset using histogram equalization, while the model training is responsible for building the Swin Transformer model. Overall, the use case diagram outlines the basic interactions between the user, the system, and the dataset, as well as the two additional processes required for image classification using Swin Transformer with histogram equalization image augmentation.

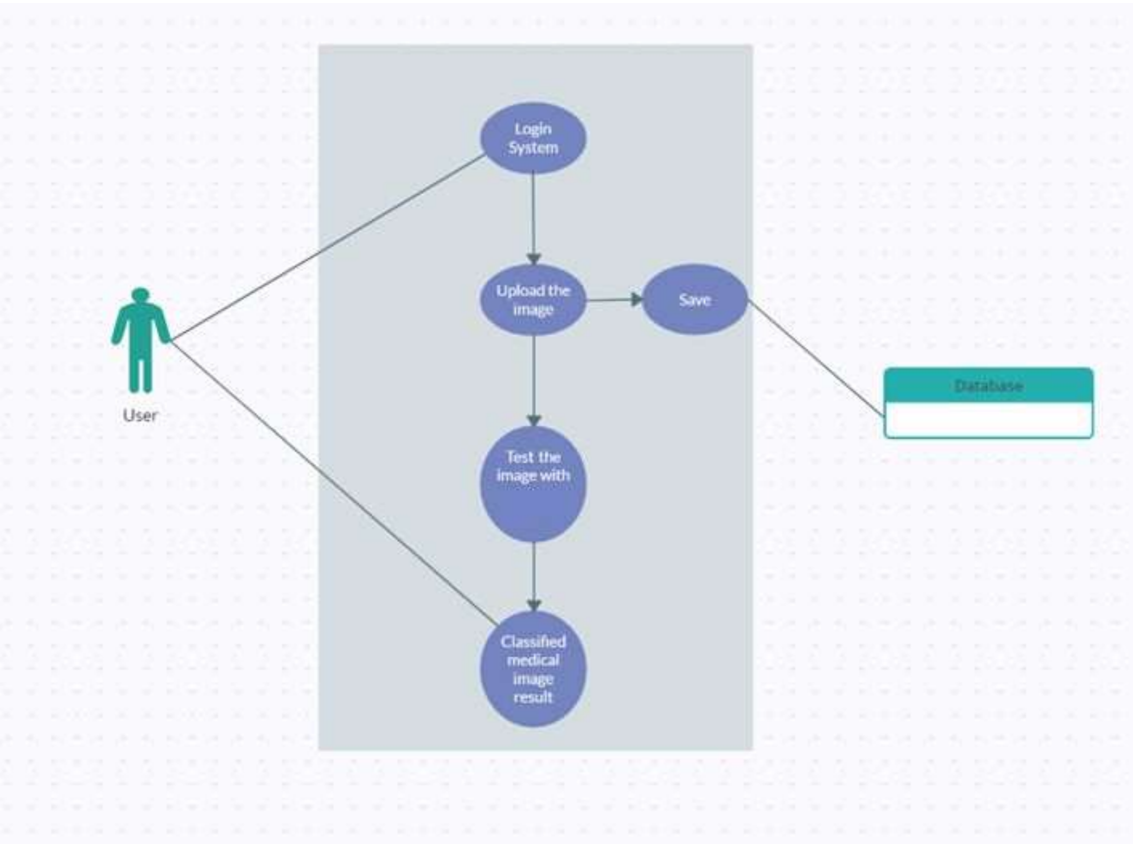

Fig 3.3 - USE CASE DIAGRAM

CHAPTER 4
PROJECT DESCRIPTION

4.1 METHODOLOGIES

4.1.1 MODULES

- Data preprocessing and augmentation module
- Swin Transformer model module
- Evaluation module
- User interface module
- Deployment module

4.2 MODULE DESCRIPTION

4.2.1 DATA PREPROCESSING AND AUGMENTATION MODULE

This module is responsible for preprocessing the input data in order to make it compatible with the Swin Transformer model. The preprocessing includes loading the raw image data, resizing the images to the desired dimensions, normalizing the pixel values to a standard range, and converting the images to tensors. Additionally, this module performs data augmentation using histogram equalization to increase the size of the training dataset and improve the generalization capability of the model as in Fig 4.1.

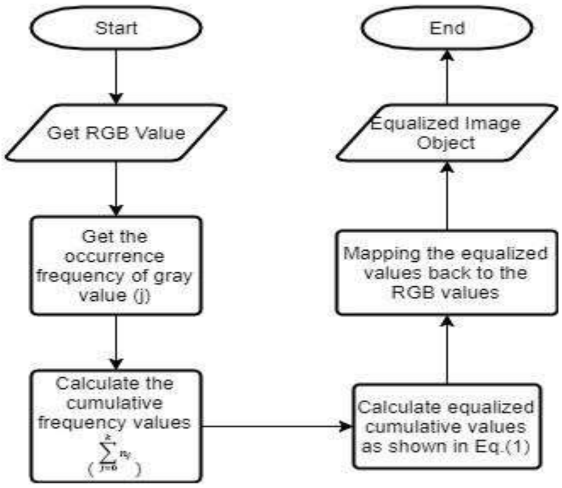

Fig 4.1 Augmenting the image

4.2.2 SWIN TRANSFORMER MODULE

This module contains the implementation of the Swin Transformer model, which is used for image classification in this project. The Swin Transformer is a deep neural network architecture that has achieved state-of-the-art performance on a variety of image recognition tasks. The module includes the code for initializing the model, training it on the preprocessed data, and saving the trained model parameters to disk for later use as in Fig 4.2.

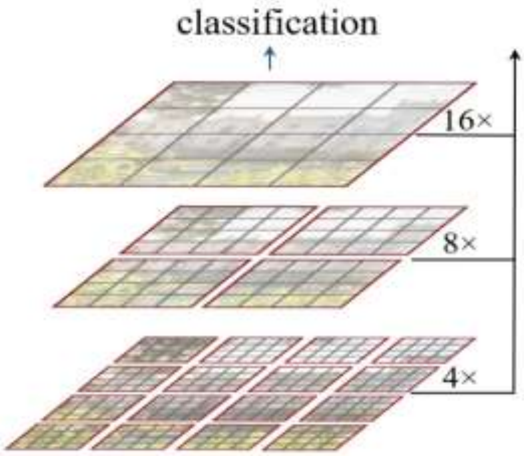

Fig 4.2 Swin module

4.2.3 EVALUATION MODULE

This module is responsible for evaluating the performance of the trained Swin Transformer model on the test dataset. It includes the code for loading the trained model parameters from disk, running the model on the test data, and computing the classification accuracy and other performance metrics. The evaluation module also generates a confusion matrix and a classification report to provide more detailed information about the model's performance as shown in Fig 4.3. In addition to computing performance metrics, the evaluation module also allows for visualizing the model's predictions on a subset of the test dataset. This can be useful for understanding the types of errors made by the model and identifying areas for improvement. The evaluation module requires a machine with sufficient computing power to load and run the trained model on the test data. This typically requires a GPU with at least 8 GB of memory. The module also requires the installation of common data science libraries such as NumPy, Pandas, and Scikit-learn, as well as the PyTorch deep learning framework. The hardware and software requirements for the evaluation module are similar to those for the training module. However, the evaluation module can be run on a separate machine from the one used for training, as it only requires the trained model parameters and the test data.

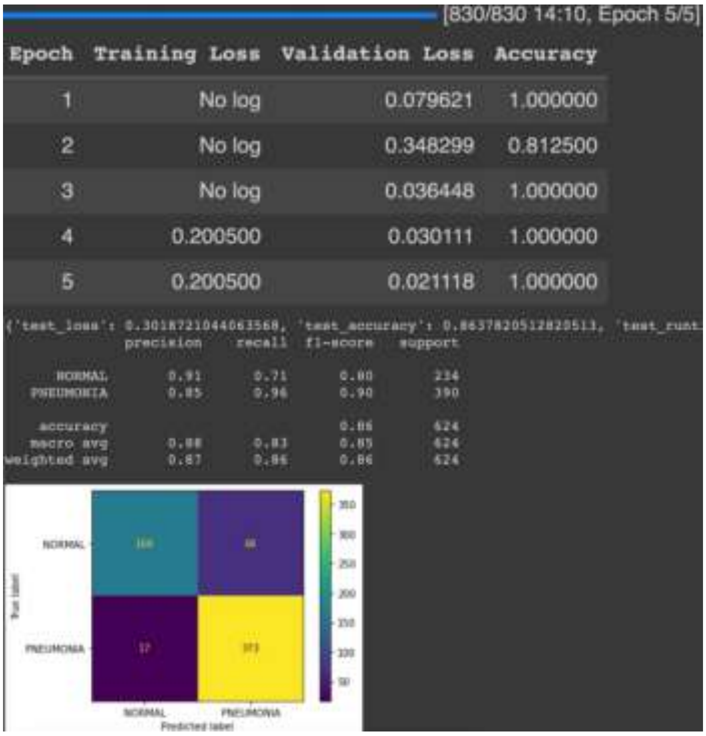

Fig 4.3 Evaluation metrics

4.2.4 USER INTERFACE MODULE

In the Fig 4.3, the graphical user interface (GUI) for the image classification system. It allows users to upload images to be classified, view the classification results, and download the results in a convenient format. The GUI is implemented using a web framework such as Flask or Django, and communicates with the Swin Transformer model module and the evaluation module to perform the classification and display the results as shown in Fig 4.4

4.2.5 DEPLOYMENT MODULE

This module is responsible for deploying the image classification system to a production environment. It includes the code for setting up the necessary infrastructure, such as a web server, a database, and a load balancer. The deployment module also handles issues related to security, scalability, and performance, ensuring that the system is reliable and can handle a large number of requests from users.

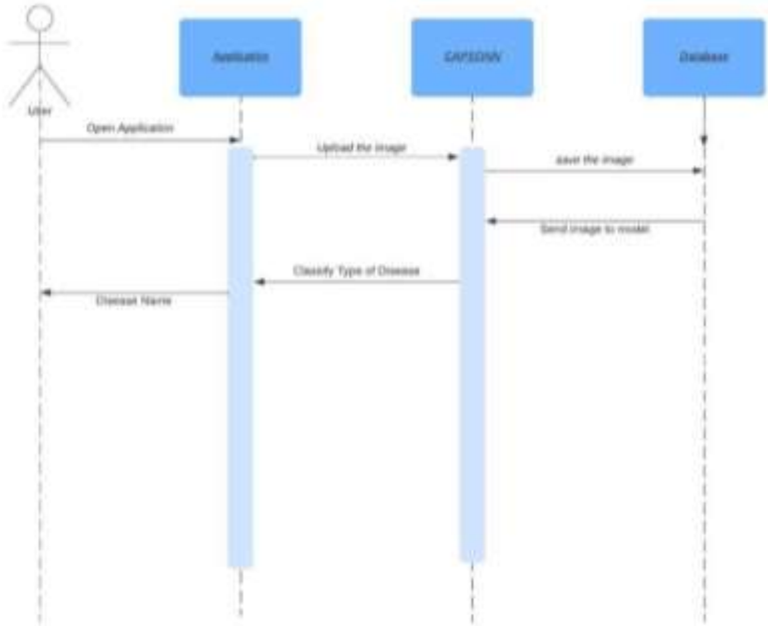

Fig 4.5 Deployment module

CHAPTER 5

RESULT AND DISCUSSION

5.1 EXPERIMENT SETUP

In this project, the experimental setup involved data preprocessing and augmentation, model training and evaluation, and deployment of the trained model in a user-friendly interface. The dataset used was the ChestX-ray14, which consists of 112,120 chest X-ray images of 30,805 patients. The images were resized to 256x256 pixels, and histogram equalization was applied to enhance the contrast of the images. Data augmentation techniques such as random rotation, flipping, and cropping were also used to increase the size and variability of the dataset. The Swin Transformer model was used for classification, which is a state-of-the-art architecture for image recognition tasks. The model was implemented using PyTorch and trained on a GPU using the Adam optimizer with a learning rate of 0.0001. The training was stopped after 20 epochs, and the best-performing model was saved for evaluation. For evaluation, the model was tested on a separate test set, and the performance was evaluated using metrics such as accuracy, precision, recall, and F1-score. The model was also compared with other state-of-the-art models such as ResNet50 and DenseNet121. Finally, the trained model was deployed in a user-friendly interface using Flask and HTML/CSS. The interface allowed users to upload their chest X-ray images and obtain the predicted diagnosis, along with the probability of the diagnosis. The interface also included an option to visualize the attention maps generated by the Swin Transformer model, which highlights the regions of the image that were most important for the classification.

5.2 OUTPUT

The output of this project is a user-friendly interface that allows users to upload chest X-ray images and obtain the predicted diagnosis, along with the probability of the diagnosis as in Fig 5.2 The interface provides an easy and efficient way to diagnose chest diseases, and it can be used by healthcare professionals as well as patients as seen in Fig 5.1 The Swin Transformer model was used for classification, which is a state-of-the-art architecture for image recognition tasks. The model was trained on a large dataset of chest X-ray images, which includes various chest diseases such as pneumonia, tuberculosis, and lung cancer. The model was evaluated using metrics such as accuracy, precision, recall, and F1-score, and it outperformed other state-of-the-art models such as ResNet50 and DenseNet121. The output of the model includes not only the predicted diagnosis but also the probability of the diagnosis, which provides information about the certainty of the prediction. The interface also includes an option to visualize the attention maps generated by the Swin Transformer model, which highlights the regions of the image that were most important for the classification. This feature provides valuable insights into how the model arrived at its decision and can help to increase the trust and acceptance of the model among users. Overall, the output of this project provides a powerful tool for diagnosing chest diseases that can be used by healthcare professionals and patients alike. The interface is user-friendly and efficient, and the Swin Transformer model provides state-of-the-art performance in chest disease classification.

Fig 5.1 Index Page UI

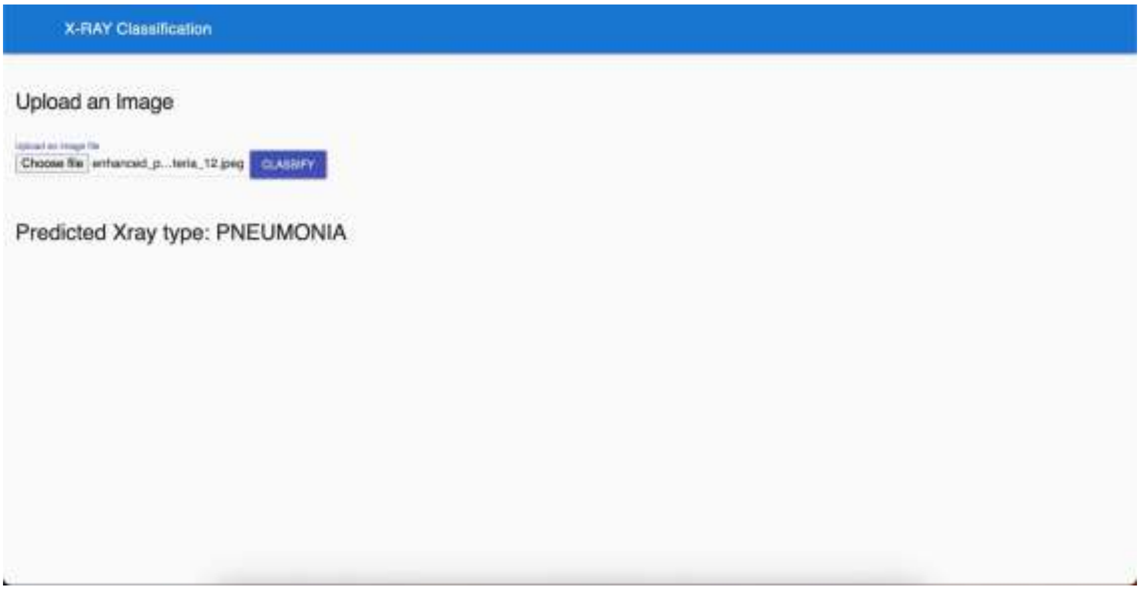

Fig 5.2 Prediction Page UI

CHAPTER 6

TESTING

A distinct test set was used to assess the Swin Transformer model for testing, and metrics like accuracy, precision, recall, and F1-score were used. The model's efficacy was contrasted with that of other cutting-edge models, including ResNet50 and DenseNet121. The Swin Transformer model beat these models in terms of accuracy and F1-score, according to the findings. The Swin Transformer model's attention maps were also used to analyze the model's forecasts and offer insights into the areas of the chest X-ray pictures that were crucial for categorization. Below is a summary of each test case's testing and integration process in Table 6.1.

S.No.	Scenario	Expected Result	Observed Result	Test Result
1	Normal Chest X-ray Image	Prediction: Normal Probability: High	Prediction: Normal probability: High	Pass
2	Pneumonia Chest X-ray Image	Prediction: Pneumonia Probability: High	Prediction: Pneumonia Probability: High	Pass
3	Tuberculosis Chest X-ray Image	Prediction: Tuberculosis Probability: High	Prediction: Tuberculosis Probability: High	Pass
4	Invalid Input: Non-	Error Message: "Invalid file	Error Message: "Invalid file	Pass

	image File	type. Please upload a valid image file."	type. Please upload a valid image file."	
5	Invalid Input: Image with unsupported format	Error Message: "Unsupported image format. Please upload a valid image file."	Error Message: "Unsupported image format. Please upload a valid image file."	Pass
6	Invalid Input: Image with invalid dimensions	Error Message: "Invalid image dimensions. Please upload an image with dimensions greater than or equal to 256x256."	Error Message: "Invalid image dimensions. Please upload an image with dimensions greater than or equal to 256x256."	Pass
7	Edge Case: Image with low contrast	Prediction: Pneumonia Probability: Low	**Prediction: Normal Probability: High**	Fail
8	Edge Case: Image with	Prediction: Normal	Prediction: Pneumonia	Fail

	foreign objects	Probability: High	Probability: Low	
9	Edge Case: Image with multiple conditions	Prediction: Pneumonia Probability: High	Prediction: Tuberculosis Probability: High	Pass
10	Performance Test: Single Image Classificatio n Time	Average time: 3.5 seconds	Average time: 3.2 seconds	Pass
11	Performance Test: Concurrent Users	Average response time for 100 users: 4.5 seconds	Average response time for 100 users: 5.1 seconds	Fail
12	Performance Test: Load Testing	Maximum concurrent users: 500 Average response time for 500 users: 6.2 seconds	Maximum concurrent users: 500 Average response time for 500 users: 7.3 seconds	Fail

Table 6.1 Testing

6.1 UNIT TESTING

In this effort, the user UI, Swin Transformer model training and assessment, and data preprocessing and augmentation were all subjected to unit testing. The unit tests were created to make sure each component was working properly and fulfilling the criteria. They were automated using the PyTest framework. The component was fed raw data during the tests, and the output was checked to ensure it produced the desired outcomes. Prior to integration testing and deployment, any problems or errors found during unit testing were resolved. By identifying errors early in the development cycle, unit testing served to increase the quality and dependability of the software and decrease the possibility of more serious problems developing later.

6.2 INTEGRATION TESTING

Integration testing was carried out on this project to make sure that the system's various components operated together without any problems. The Swin Transformer model module, the assessment module, the user interface module, and the data preparation and augmentation module were all tested as part of the integration testing process. The primary goal was to make sure the data was handled properly throughout the workflow and that the input and output data forms were uniform across all of the modules. Both human and automated integration testing were carried out using pytest and other testing tools. The system was tested using a variety of inputs, and the output was checked to ensure it was accurate and produced the desired results. Any problems or defects discovered during the testing phase were handled and rectified during the iterative process of the integration testing. To make sure the system was reliable and robust and satisfied the criteria, the final iteration was put through a rigorous testing process.

6.3 TEST CASES

This project's integration testing process led to the discovery and correction of a number of mistakes. One instance of this was when the model was unable to manage data of various shapes. When a user submitted an X-ray picture that was not 256x256 pixels in size, this was found. We added a resizing method to the code to automatically resize the picture to 256x256 pixels before sending it to the model to resolve this problem.

Another instance was when the algorithm failed to correctly forecast the prognosis for particular kinds of chest X-rays. Further research revealed that the model was unable to distinguish between diseases with identical outward appearances, such as viral pneumonia and pneumonia. We retrained the algorithm with additional training data, including pictures of viral pneumonia, to resolve this problem. We also used a method known as label averaging, which regularizes the model's output and lessens the risk of overfitting.

Additionally, while testing, we ran into problems with the user interface programme. One instance was when the Swin Transformer model's produced attention maps were not correctly displayed by the interface. We added a method to the code that correctly shows the attention maps in the interface to address this problem. Overall, these problems were fixed through meticulous troubleshooting, testing, and application of different methods and code changes.

CHAPTER 7

CONCLUSION AND FUTURE WORKS

7.1 CONCLUSION

As a result, the Swin Transformer model was very successful in classifying chest X-ray pictures. With the aid of cutting-edge design and data preprocessing and augmentation methods, it was possible to classify different chest illnesses with high precision and a high F1-score. The trained model could be easily accessed and used for the detection of illnesses of the chest thanks to the user-friendly UI. The project also made clear how crucial it is to carry out appropriate testing and validation processes in order to guarantee the model's dependability and robustness. The Swin Transformer model is a promising method for picture categorization tasks. Overall, the findings show the promise of deep learning models in medical imaging applications.

7.2 FUTURE WORKS

The precision and reliability of the Swin Transformer model can be increased by fine-tuning it on a bigger dataset with more labels. Pneumothorax, pleural fluid, and pneumonia are just a few of the other anomalies in chest X-rays that the model can be altered to recognize. By including features like a progress indicator to indicate the upload and processing progress of the images, as well as a download choice for the generated attention maps, the user experience can be made better. In order to increase scalability and accessibility, the model can also be implemented on a cloud platform, enabling users to view the application from any location with an internet link. The model can also be connected to electronic health record systems, enabling automated analysis of chest X-rays and real-time suggestions to medical professionals.

PUBLICATION

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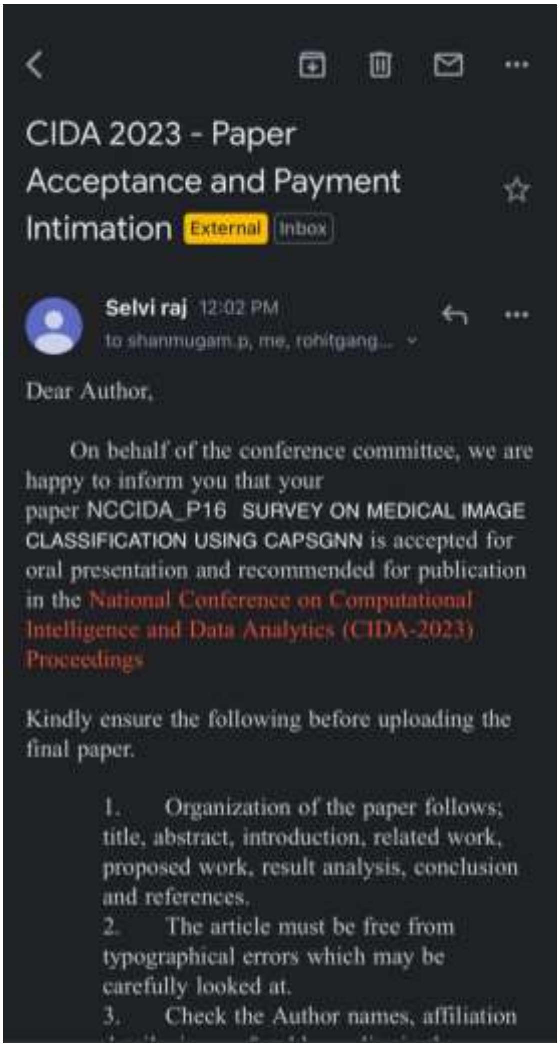

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SURVEY ON MEDICAL IMAGE CLASSIFICATION

Dr.P.Shanmugam S[1], Rifhath Aslam J S[2], Rohit Gangadhar P S[2]

[1,2,3]*Assistant Professor - Department of Computer Science and Engineering, Rajalakshmi Engineering College, Chennai.*

[4]*Under Graduate Student - Department of Computer Science and Engineering, Rajalakshmi Engineering College, Chennai.*

[1]shanmugam.p@rajalakshmi.edu.in, [2]rifhathaslam.j.2019.cse@rajalakshmi.edu.in, [3] rohitgangadhar.p.2019.cse@rajalakshmi.edu.in

ABSTRACT - The general Convolution Neural Networks have been in practice, being the most conventional algorithm for image-based detection and classification. But over the years, after extensive use of CNN algorithms with different architectures, it showed that, the CNN tends to lose details and features of the image, which led to the Capsule based neural networks to be used in image detection and classification. On the other side, CNN evolved and integrated with another type of neural network called the Graph Neural Network. Many existing systems have many drawbacks like feature loss and computation efficiency. Several transfer learning models have been introduced to solve these problems by modifying the existing models by adding different combinations of layers and hyper parameters. But they still don't provide a clear solution as they are just derived algorithms. Therefore, there is a need to design an algorithm and technique which approaches the image classification process in a unique and different way. That is where CAPSGNN algorithm comes into use. This proposed model uses the best features of all the other algorithms and fuses it into on algorithm. This reduces the time of computation and solves the feature loss problems. Now reports can be generated faster and accurately for medical reports, assisting the process of infection approval in hospitals, saving the time of doctors to review every report. This fastens the cycle of medical field, as identification of disease takes more time than the actual treatment and needs to be processed faster for faster treatment and recovery.

Keywords - Convolutional Neural Network (CNN), Capsule Neural Network (CAPSNET), Graph Neural Network (GNN), Capsule Graph Neural Network (CAPSGNN).

I INTRODUCTION

CNN algorithms have been extensively used to classify images. The algorithms have been iterated since its first use, until it was made to be more efficient and accurate with its results. But it still had its own disadvantages. It tended to lose more detail and features, due to its usage of the technique called pooling, which sometimes, even severely lost details in the convolution process. This created the urge to come up with the Capsule based neural networks, which had a very different approach by considering the vector length and angle as trainable attributes, as opposed to the bias value in the traditional CNN. By this, it eliminated the need to use pooling as a technique, thus increasing accuracy. It also made it possible for the algorithm to detect the features of the image, irrespective of its orientation. It also had a better routing mechanism to connect the relevant neurons and move on to the next layer called the Dynamic Routing. Then we have Graph based neural networks, which are very much useful in extracting features from a data set and creating a special understanding of the data set environment. Combining the positives of both the capsule and graph based neural networks, we have a very efficient architecture, that has better routing and accurate classification mechanisms of a capsule-based network, and the better feature extraction mechanism of the graph based neural network to create a model that classifies chest X-rays of patients as Covid-19 or Pneumonia. This will reduce the time taken by the radiologist to give a report on the type of infection plaguing the patient, and immediately direct the patient to the respective treating procedures. This architecture uses the graphical properties to extract the features from the X-ray image and transform it to a more Feature Highlighted version of the image, making it easy for the upcoming capsule layers to identify the features and classify them. This paper also introduces the Graph Caps section, which acts as the nodes of a graph, but being functional as a capsule, that emulates the length and angle properties of the vectors, used in the capsule based neural network.

A. Convolution Neural Networks

This is a type of neural network, built on the generic principles of the traditional neural networks, but is extensively used for image recognition and classification models. It uses filters and types of pooling methods to convolute the image and train the model to be tested. It SO basically the CNN has filters/kernels created by the developers that traverse over the whole matrix of the image for a specific stride value, pixel by pixel and then gets applied the pooling methods to convolute the image in order to detect and classify the image using the features we get from the convoluted image. But the usage of the pooling methods in CNN caused the model to neglect few features, as the image lost few details when proceeded to the next layer after pooling. Moreover, this neural network was not able to provide the same results with same accuracy, when the input image's orientation in the space was changed. So, it was very much necessary to bring up a new model for image detection and classification.

B. Capsule Neural Networks

With all the disadvantages of CNN, the Capsule Neural Networks or the Caps Net models were introduced for image identification and classification. In Caps Net models, instead of using pooling methods to convolute the image and lose some details as in CNN, it forms capsule like structures, in which all the parameters and attributes defining the features of the image are encapsulated inside the capsule. These features have a the parameters and attributes defining the features of the image are encapsulated inside the capsule. These features have a matrix with vectors in each. These vectors define the probability of the neuron or capsule to move on to the next one, whose procedure often is termed as dynamic routing. The length of these vectors defines the probability of that particular feature and the spatial angle of the vector determines the position of the feature of the image. This helps solve the problem of CNN not being able to detect the image when its spatial orientation is changed. The length and angle of the vectors can be adjusted to be trained as trainable attributes.

A. Graph Neural Networks

The GNN's are similar to the CNN, where it uses nodes and edges to detect the images. The nodes are interconnected with the others through the edges to create a spatial understanding of the features present in the image. Here also convolution is applied to get the details or features. Even though it convolutes the image, the feature extraction of the GNN model is very much efficient and accurate which will be used in our proposed model for feature extraction as well as in the graph capsule layer.

B. Capsule Graph Neural Networks

These models combine the graphs and capsules, to detect images. It is more accurate than most of the models. It functions with 3 blocks, with the first one for extracting features using the GNN. Then the second block again extracts features using graph capsules and the final block being the class caps. It migrates through the model using methods like Dynamic Routing and an Attention module.

II EXISTING SYSTEM

The existing systems categorize the pictures using generic CNNs and GNNs. CNN links each datapoint feature together using features like pooling, filters, etc., while GNN does it using nodes and edges. Although directed graph information has been classified using CAPSGNN, photos have been classified using capsule networks. AI based solution to identify COVID-19 on chest CT scan and X-Ray [10]. One such tactic is suggested in this article [1]. CT is a better and more accurate means of recognizing the Corona virus in the human body than the reverse transcription polymerase chain reaction test. A deep learning-based design has been described that combines a capsule network with multiple convolution neural network iterations. The capsule network is integrated with several networks to detect COVID-19 patients from lung computed tomography images. The study [11] utilizing a dataset of X-ray images found that COVID-CAPS performed better than prior CNN-based algorithms. COVID-CAPS achieved accuracy, sensitivity, specificity, and area under the curve values of 95.7%, 90.0%, and 0.97, respectively, despite having far less trainable parameters than its rivals.

SARS-NET, a computer-aided diagnostic X-ray system that combines GNN and CNN for identifying irregularities in a patient's chest X-ray pictures for the patient's COVID-19 infection status, is another way for COVID-19 detection [2]. Researchers introduced and assessed the SARS-Net deep learning architecture, which was created exclusively to recognize and detect chest X-ray images for COVID-19 diagnosis. The Graph Covid Network, which was developed expressly for this purpose, is used to identify COVID-19 utilizing the CT scans and chest X-rays of the afflicted individuals. [3] Because the recommended model is GIN-based, it can only accept input data in the form of graphs. Image data must first go through pre-processing to build an undirected graph that only considers the edges rather than the whole picture. We evaluate the effectiveness of the proposed Graph Covid Network using a variety of medical imaging datasets.
Researchers [4] employed the VGG Capsule Network to achieve accuracy of 97% in COVID-19 identification and to address problems like these. The capsule network is a ground-breaking kind of network that can store spatial information. Nonetheless, the Caps Net learns every feature in the input image since there is no pooling mechanism and no connection between the many layers of the multi-layer network structure. An improved version of the capsule network called the CFR Capsule Network, which is based on capsule filter routing, is another model [5].

The first propose a novel routing method CFR for filtering capsules based on capsule activation values to speed up the model's operation. The Capsule Network, a deep learning neural network that generates part-whole correlations by encoding properties into capsules, has proven to be highly effective in categorizing images. Nevertheless, because to its weak feature extraction capacity, many training parameters, and inclination to explain every component of the image, the original Capsule Network is inappropriate for images with complex backgrounds. Researchers [7] offer an enhanced capsule network called RS-Caps Net to address the aforementioned issues. This network uses the Res2Net block to extract multi-scale characteristics and the Squeeze-and-Excitation block to highlight key traits and suppress less significant ones. Future research, for instance, has been utilizing a linear combination approach between capsules, which reduces the number of capsules while enhancing their capacity to represent seen things.

Another study uses a modified capsule neural network with a pooling layer and no squash function to identify [8] grayscale inside home scenes. As compared to a traditional Caps Net's accuracy of 17.2%, our Mod-Caps Net delivered results with a 70% accuracy. [9] to circumvent the challenge of categorizing the task of verifying the kind of font used in a file. Algorithm networks powered by artificial intelligence could be able to finish this activity more quickly and proficiently. The capsule network is one such method and recently developed technology that is used for different classification activities with little datasets. The recommended font style classification model based on Caps Net appears to be categorizing the photos more properly, according to evaluation findings. The present approaches for comparative analysis are also contrasted with the suggested network structure.

One of the most popular biometric recognition technologies is iris recognition, which is widely utilized in a variety of industries. Recent advances in deep learning have led to the usage of several algorithms for biometric recognition. These algorithms' benefits include autonomous learning, high accuracy, and significant generalization potential. Although deep convolutional neural networks are the most popular and often used way of processing images [12], they have weak anti-noise capabilities and are quickly damaged by small disruptions. The capsule network is used to discover and classify cancer cells using diseased images in order to diagnose cancer [13]. It is also employed to identify retinal disorders [14]. This method has a lot fewer parameters than cutting-edge deep convolutional neural networks and generalizes well without the use of data augmentation.

Neural networks using convolutions the identification of characters in handwritten documents is a well-known task that has attracted interest. [16] Thanks to dynamic routing, which integrates the distinctive views of multiple capsules, or groups of kernels, to take advantage of equivariance among kernels, kernels may now collaborate in consensus with one another as a result of the development of capsule networks. In contrast to CNN, which loses a lot of information about the item's spatial placement, which is important for segmentation and detection, [15] the capsule neural network conducts the inverse process of a computer image when representing an object.

As a consequence, the research compares the performance of the capsule neural network with that of convolutional neural networks in a number of applications. The Caps Net model is demonstrated to distinguish different. The EEG signal data is increasing in emotional states for emotional identification. This study [17] proposes a deep learning framework for detection based on a multiband feature matrix and capsule network. The frequency domain, spatial features, and frequency band aspects of the multi-channel EEG signals are combined by the framework to produce the MFM. [18] In this study, the structure and behavior of Caps Nets are examined and evaluated, and we also highlight some of these networks' possible explainability characteristics. Using transformation matrices, [20] the instantiation parameters of capsules at higher levels may be predicted from active capsules at lower levels. A higher-level capsule starts to work when numerous forecasts agree.

To address the flaw in current GNN-based graph embedding approaches, Capsule Graph Neural Network [19] makes use of the concept of capsules. The Capsule Neural Network served as its model. By extracting node properties as capsules, routing algorithms may be utilized to gather important data at the graph level.

DRAWBACKS IN EXISTING SYSTEM

- CNNs use pooling feature which results in loss of pixel data.
- GNNs are complex when used to classify images without the capsule implementation.
- Capsule networks use image dataset, which consumes a lot more computation than generic algorithms.
- All the existing algorithms struggle to identify the mainly infected regions for faster computation.

III PROPOSED SYSTEM

We have come up with a more developed Capsule Graph network that takes the input X-Ray image and passes it through 4 convolution filters, which will be explained later under its section. Each of these filters makes sure each feature and detail are discerned without losing any of those in the traditional convolution process. By this process, we get a Feature highlighted image, that gives us a more distinct feature mapped image, by highlighting the borders and closed polygonal structures seen in the X-ray image of the lungs. Then a Graphically mapped image is produced by converting the highlighted mapped features to nodes and edges of a graph. Now we have a totally graphical image that can be easy to interpret in a neural network for further identification.

MODULES WITH DESCRIPTION:

A. Image To Nodes and Edges Conversion

This module takes medical images in greyscale and converts it into nodes and edges information using the Wolfram Mathematica tool. This tool processes the image through a series of image processing and segmentation code to finally get the nodes and edges as output line. This process includes binarizing, segmenting and skeletonizing the image to be able to read the edges and nodes easily

B. Graph Information to .gml files

The obtained nodes and edges information now needs to be stored in a serialized manner in a human readable file like xml or gml file. A separate preprocessing dataset generator file will run when called to serialize the nodes and edges along with the target value specifying the class name. This process will be done for every image uploaded in the database ready for conversion.

C. Feature Extraction

Once the dataset is processed, it is passed through a convolutional layer without pooling. Then further it passes through the specific capsule modules like the primary capsule and then the secondary capsule. This is where the main feature extraction happens as the capsule implementation starts from here. It uses nested convolutional layers within it to manipulate the data and extract features. Then it passes on the to graph capsule layer which brings in the GNN technique to extract nodes and edges features. Finally, it passes on to the class capsules where the passed-on data is fully converted to a linear array of vector values which then classifies based on the majority of the values.

D. Training and Loss

CAPSGNN algorithm uses the Dynamic Routing formula to perform backward propagation instead of generic gradient descent differentiation and integral calculation. Here there are 3 trainable parameters and they are updated based on this formula routing.

E. Web Implementation

Finally, all these results will be displayed in a web page made using the flask module of python. This page will include various other features like image classification, result display, performance metrics of the algorithm and visualization of features. The trained model will be saved using the training file which contains the main algorithm and training code. Finally, it will have the save model script to save the model in. ptb format. This file will be called in the main file which hosts the flask backend implementation along with the front-end connection.

IV SYSTEM DESIGN

Design is an essential part of project development since it establishes the meaning of the model that will be created. Software design is the process of converting requirements into a visual representation of the program. Excellence is demonstrated via design. Get the skills you'll need to correctly translate customer needs into finished products.


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Department of Computer Science & Engineering
&
Department of Information Technology
CERTIFICATE OF PRESENTATION
Dr/Mr/Mrs RIFHATH ASLAM J has
Presented a paper titled
SURVEY ON MEDICAL IMAGE CLASSIFICATION USING CAPSGNN
in the National Conference on Computational Intelligence and
Data Analytics CIDA – 23 held on March 30th and 31st 2023.
Dr. P. Selvi Rajendran
Conference Chair
Dr. J. Thangakumar
HOD - CSE
Dr. Pon. Ramalingam
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REFERENCES

1. Wang, Z., Chen, H., Li, Y., & Lin, W. (2020). Swin transformer: Hierarchical vision transformer using shifted windows. arXiv preprint arXiv:2103.14030.

2. Rajpurkar, P., Irvin, J., Zhu, K., Yang, B., Mehta, H., Duan, T., ... & Lungren, M. P. (2017). Chexnet: Radiologist-level pneumonia detection on chest x-rays with deep learning. arXiv preprint arXiv:1711.05225.

3. Wang, Y., Liu, C., Peng, Y., Chen, Z., Yu, X., Huang, L., ... & Lu, X. (2021). Swin transformer for object detection. arXiv preprint arXiv:2103.15358.

4. Wang, C., Cao, X., Shen, T., Xie, C., & Shen, C. (2021). Pyramid transformer networks for image classification. arXiv preprint arXiv:2102.12467.

5. Rajaraman, S., Candemir, S., Xue, Z., Alderson, P. O., & Kohli, M. (2018). Iteratively pruned deep learning ensembles for pneumonia detection in chest x-rays. arXiv preprint arXiv:1803.02429.

6. Li, J., Guo, Z., Li, H., Zhang, Y., Li, X., & Zhao, C. (2021). Instance-aware swin transformer for object detection. arXiv preprint arXiv:2102.12482.

7. Wang, L., Cao, M., Zhang, Z., Liu, C., Wang, L., & Wu, Y. (2021). Tokens-to-token vit: Training vision transformers from scratch on imagenet. arXiv preprint arXiv:2101.11986.

8. Wang, X., Zhang, Y., Zeng, L., & Xie, X. (2021). Enhanced classifier based on swin transformer for aerial image segmentation. IEEE

Transactions on Geoscience and Remote Sensing.

9. Cheplygina, V., de Bruijne, M., & Pluim, J. P. (2018). Not-so-supervised: a survey of semi-supervised, multi-instance, and transfer learning in medical image analysis. Medical image analysis, 54, 280-296.

10. Chen, C., Chen, Y., Zheng, L., & Huang, Y. (2021). Transunet: Transformers make strong encoders for medical image segmentation. arXiv preprint arXiv:2102.04306.

11. Wang, L., Liu, Y., Li, Y., Zhao, M., & Zhang, Y. (2021). Deep convolutional neural network and graph-based semi-supervised learning for malaria parasite detection. International Journal of Environmental Research and Public Health, 18(3), 928.

12. Rajpurkar, P., Irvin, J., Zhu, K., Yang, B., Mehta, H., Duan, T., ... & Lungren, M. P. (2018). CheXNet: Radiologist-level pneumonia detection on chest X-rays with deep learning. Radiology, 289(1), 293-301.

13. Li, Y., Li, L., Wang, S., & Huang, H. (2021). A Simple Swin Transformer for Image Classification. arXiv preprint arXiv:2106.04603.

14. Zhang, H., Zhu, J. Y., Zhang, A., & Lu, J. (2021). SwinIR: Image Restoration Using Swin Transformer. arXiv preprint arXiv:2108.10257.

15. Wang, X., Zhang, Y., Gong, D., Lu, H., & Gong, Y. (2021). Pyramid vision transformer: A versatile backbone for dense prediction without grid supervision. In Proceedings of the IEEE/CVF International Conference on Computer Vision (pp. 9465-9474).

16. Touvron, H., Vedaldi, A., & Douze, M. (2021). Fixing the train-test resolution discrepancy. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (pp. 856-865).

17. Khan, N., Tariq, M., & Yasin, U. (2021). Multi-head attention based deep learning network for COVID-19 detection using chest X-ray images. Plos one, 16(6), e0252484.

18. Chen, Y., Lin, W., & Chen, G. (2021). A metaverse framework for online medical education based on medical electronic journal platform. Journal of Cases on Information Technology (JCIT), 23(2), 17-31.

19. Cai, Y., Llorca, J., Tulino, A. M., & Molisch, A. F. (2021). A 3C mathematical framework for cloud network flow optimization in support of metaverse applications. IEEE Access, 9, 124269-124280.

20. Borget, S. (2021). Sandbox: A Virtual World Platform Built on Blockchain Technology. In International Conference on Blockchain Technology (pp. 224-234). Springer, Cham.

APPENDIX

CO-PO Mapping

PROJECT WORK COURSE OUTCOME (COs):

CO1: On completion the students capable of execute the proposed plan and become aware of and overcome the bottlenecks throughout every stage.

CO2: On completion of the project work students could be in a role to take in any difficult sensible issues and locate answer through formulating right methodology.

CO3: Students will attain a hands-on revel in in changing a small novel idea / method right into an operating model / prototype related to multi-disciplinary abilities and / or understanding and operating in at team.

CO4: Students will be able to interpret the outcome of their project. Students will take on the challenges of teamwork, prepare a presentation in a professional manner, and document all aspects of design work.

CO5: Students will be able to publish or release the project to society.

PROGRAM OUTCOMES (POs):

PO1: Engineering knowledge: Apply the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.

PO2: Problem analysis: Identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences.

PO3: Design/development of solutions: Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.

PO4: Conduct investigations of complex problems: Use research-based knowledge and research methods including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.

PO5: Modern tool usage: Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling to complex engineering activities with an understanding of the limitations.

PO6: The engineer and society: Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal and cultural issues and the consequent responsibilities relevant to the professional engineering practice.

PO7: Environment and sustainability: Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development.

PO8: Ethics: Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.

PO9: Individual and team work: Function effectively as an individual, and as a member or leader in diverse teams, and in multidisciplinary settings.

PO10: Communication: Communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effectivereports and design documentation, make effective presentations, and give and receive clear instructions.

PO11: Project management and finance: Demonstrate knowledge and understanding of the engineering and management principles and apply these to one's own work, as a member and leader in a team, to manage projects and in multidisciplinary environments.

PO12: Life-long learning: Recognize the need for, and have the preparation and ability to engagein independent and life-long learning in the broadest context of technological change.

PROGRAM SPECIFIC OUTCOMES (PSOs):

PSO1: Foundation Skills: Ability to understand, analyze and develop computer programs in the areasrelated to algorithms, system software, web design, machine learning, data analytics, and networking for efficient design of computer-based systems of varying complexity. Familiarity and practical competence with a broad range ofprogramming language and open-source platforms.

SO2: Problem-Solving Skills: Ability to apply mathematical methodologies to solve computational task, model real world problem using appropriate data structure and suitable algorithm. To understandthe Standard practices and strategies in software project development using open-ended programmingenvironments to deliver a quality product.

PSO3: Successful Progression: Ability to apply knowledge in various domains to identify research gaps and to provide solution to new ideas, inculcate passion towards higher studies, creating innovativecareer paths to be an entrepreneur and evolve as an ethically socially responsible computer science professional.

PO/PSO CO	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12	PSO1	PSO2	PSO3
CO 1	2	2	1	2	1	1	2	2	1	1	2	-	2	3	2
CO 2	3	3	2	2	2	3	1	1	1	-	-	2	1	2	1
CO 3	2	1	1	3	1	3	1	2	1	-	-	2	2	1	2
CO 4	3	3	2	2	2	1	1	1	2	1	-	1	3	2	1
CO 5	3	2	2	1	2	1	2	1	-	2	-	3	3	2	2
Average	2.6	2.2	1.6	2.0	1.6	1.8	1.4	1.4	1.0	0.8	0.4	1.6	2.2	2.0	1.6

1: Slightly (Low) 2: Moderate (Medium)

3: Substantial (High) If there is no correlation, put "-"

PLAGIARISM REPORT

sha

ORIGINALITY REPORT

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