Traumatic Meningeal Enhancement Detection by Deep Learning-based Biomedical Image analysis and Handcrafted Features Extraction

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A thesis submitted to the Department of Computer Science and Engineering
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Declaration

It is hereby declared that

1. The thesis submitted is my/our own original work while completing a degree at Brac University.

2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.

3. The thesis does not contain material that has been accepted, or submitted, for any other degree or diploma at a university or other institution.

4. We have acknowledged all main sources of help.

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Approval

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Ethics Statement

Our research confirms the claim made, and all cited and referenced papers and sources are accurate. The work has never been submitted for a degree to any other college or academic organization. The four co-authors acknowledge and accept any violations of the thesis rule. In addition, we would like to take this chance to thank everyone who has supported us through this process. We finished our thesis without committing to any illegal techniques. Our work complies with the ethical standards of Brac University.

Abstract

Traumatic Meningeal Enhancement (TME) is a critical medical condition characterized by abnormal enhancement of the meninges following trauma, often observed in medical imaging studies. Traumatic meningeal injuries result from external forces hitting the head or skull, damaging the brain's protective coverings. These injuries can come from falls, car accidents, sports injuries, attacks, or other head trauma. Even in the absence of further trauma-related cerebral abnormalities, TME may be visible on an acute MRI. In addition to highlighting some of the present considerations and unresolved issues of using them, this research aims to address some of the prospective applications of more sophisticated imaging in traumatic meningeal enhancement (TME). A deep convolutional neural network (CNN) model that uses a dataset of 7800 images is used in this study. Testing and training are the two discrete parts of the dataset. We have used the appropriate augmentation method to construct the dataset. Three categories have been used to categorize the data in this study: normal, early (pre), and acute (post). We divided the 6,000 images into three categories for training: normal, early (pre), and acute (post). 30% of the data was used for testing, while the remaining 70% was used for training. The dataset was evaluated against five different transfer learning models and a customized CNN model known as the 13-layered CNN model in the research. We evaluated four transfer learning models, namely VGG19, VGG16, InceptionV3, and MobileNet, using an identical dataset. The accuracy rates obtained were 84%, 86%, 80%, and 89% respectively. Utilizing the same dataset, we proceeded to ensemble these pre-trained models and it obtained 88.83% accuracy. Surprisingly, even with the ensemble, our customized CNN model exhibited superior accuracy. Additionally, we conducted SVM and XG Boost hand-crafted feature extraction using techniques like positional orientation (PO), histogram of oriented gradients (HOG), and mean pixel value (MPV). SVM obtained accuray of PO,normal:67% early(pre): 65% and acute(post):67%, for HOG, normal:81% early(pre): 75% and acute(post):77%, for MPV, normal:71% early(pre): 70% and acute(post):70%. XGBoost obtained accuracy of PO,normal:63% early(pre): 60% and acute(post):57%, for HOG, normal:72% early(pre): 69% and acute(post):70%, for MPV, normal:66% early(pre): 63% and acute(post):62%. Subsequently, we applied Support Vector Machine (SVM) and XGBoost algorithms for feature extraction. Despite these efforts, our CNN model consistently outperformed the models built using these feature extraction methods. In contrast, our newly customized CNN model demonstrated a remarkable accuracy of 91%. These results illustrate that when it comes to image processing, our CNN model performs better than any other model in identifying traumatic meningeal brain enhancement.

Keywords: TME; CNN; Meningeal; Deep Learning; Pre-trained; feature extraction; Image Processing; Transfer Learning

Dedication

We dedicate this research to the strong and resilient ones who have suffered severe meningeal traumatic brain injuries and their families; their determination motivates us to improve methods for identifying these injuries. We would like to express our gratitude to our families, friends, supervisor, and co-supervisor for their constant encouragement, support, and guidance in helping us finish our thesis. To improve the lives of those who suffer from traumatic meningeal brain injuries, your courage motivates us to keep working towards better detection.

Acknowledgment

First and foremost, we are thankful to the Almighty for giving us the chance and the path we needed to finish this project on time. Secondly, we would like to sincerely thank our thesis supervisor, Dr. Mohammad Golam Robiul Alam, and co-supervisor, Md. Tanzim Reza, for their constant encouragement, mentorship, and guidance as we explored a challenging topic. Their relentless assistance and continuous input enabled us to conquer the challenges. Thirdly, we intend to use this opportunity to express our gratitude to every faculty member for their assistance and support during our stay at Brac University. Finally, we would like to thank our beloved parents for their unwavering support, encouragement, and prayers.

Nomenclature

$*$ Multiplication
/ Division
2D - two-dimensional
TBI - Traumatic Brain Injury
TMI - Traumatic Meningeal Injury
TME - Traumatic Meningeal Enhancement
FLAIR - Fluid attenuated inversion recovery
T1WI T1 - weighted image
mTBI - Mild Traumatic Brain Injury
CNN - Convolutional Neural Network
CT - Computed Tomography
MRI - Magnetic Resonance Imaging
VGG - Visual Geometry Group
Colab - Collaboratory
CONV - Convolutional
DesNet - Densely Connected Convolutional Networks
GPU - Graphics processing unit
ReLu - Rectified Linear Activation Function
RGB -Red Green Blue
HOG - Histogram of Oriented Gradients
PO - Principal Objective
MPV - Mean Pixel value
SVM - Support Vector Machines
XGBoost - Extreme Gradient Boosting

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Chapter 1

Introduction

Traumatic meningeal eenhancement is a very intricate diagnostic challenge within the realm of biomedical imaging. Despite the notable reduction in the occurrence and death rates of meningitis in recent decades, particularly in high-income countries, it remains a medical emergency. Early diagnosis and swift treatment are essential to prevent fatalities or significant neurological complications. Traumatic meningeal enhancement presents a global diagnostic challenge due to its subtle appearance in biomedical images, necessitating expertise for accurate interpretation. There is a chance of misdiagnosis or delayed diagnosis since current imaging methods frequently lack the accuracy required to identify these subtle variations. More flexible and effective diagnostic techniques are needed because of the complexity and diversity of these improvements, which make precise diagnosis even more difficult. Improving detection accuracy, speed, and speed through the use of innovative techniques like the CNN deep learning approach is the aim of resolving these problems. This might revolutionize the way traumatic meningeal enhancement is diagnosed and treated worldwide. Meningeal enhancement may be visible on a contrast-enhanced MRI among people who have had an acute traumatic brain injury, even in situations where a head CT scan reveals no brain damage [13].

Meningeal enhancement can result from a variety of causes, most commonly from severe head or spinal trauma. The brain and spinal cord are surrounded by layers of tissues, known as the meninges, which may become inflamed or damaged as a result of these traumas. Traumatic meningeal injuries are frequently seen in situations involving falls, accidents, sports injuries, or physical trauma, while the precise number of victims varies. Severe headaches, stiff necks, light sensitivity, altered mental states, and, in extreme situations, potentially fatal illnesses like bleeding or meningitis are among the symptoms of such injuries. Meningeal injuries are treated by treating the underlying cause, controlling the symptoms, and, in rare circumstances, performing surgery to heal the damage. On the other hand, the severity and rapidness of medical intervention have a major impact on the expected outcome and recovery. To treat traumatic meningeal enhancement promptly and effectively, detection is essential. By identifying subtle patterns in biological images, CNN-based detection improves accuracy and enables early and accurate diagnosis for better patient outcomes. In 2020, there were 69,473 deaths and 214,110 hospitalizations connected to traumatic meningeal brain injury (TMI), with roughly 586 hospitalizations and 190 deaths every day, according to the latest recent data. With 32% of hospitalizations and 28% of deaths associated with TBI, people 75 years of age and older had the highest rates and quantities of these events. Compared to females, men had three times the risk of dying from a TBI and almost double the chance of being admitted to the hospital [23]. Traumatic meningeal injury (TMI) is the "silent epidemic" that is more responsible than any other acute insult for deaths and disabilities around the world. However, it is still unknown how common TMI is and how it varies by geography and socioeconomic status.

In recent years, handcrafted feature extraction methods have faced limitations in effectively capturing intricate and abstract features from complex images, leading to reduced adaptability to diverse datasets and the potential loss of essential information. Furthermore, pre-trained models frequently needed help adjusting to specific domains and scaling to new tasks, even though they were effective at learning general features from huge datasets. But instead of requiring challenging feature engineering, convolutional neural networks (CNNs) were developed as a solution by automatically learning discriminative features from unprocessed data. CNNs are particularly good at capturing abstract and hierarchical representations, which allows them to adjust to different tasks and datasets with flexibility. CNN's adaptability and automatic feature learning have overcome the drawbacks of handcrafted feature extraction and pre-trained models, enhancing their efficacy in image analysis applications, including the diagnosis of traumatic meningeal brain injuries. For example, in a research study, on pneumonia diagnosis from chest X-rays, custom characteristics such as texture analysis or particular pixel intensities may not be able to capture tiny patterns suggestive of the illness. The fine-grained information necessary for pneumonia diagnosis in X-rays may be absent from pre-trained models that were first trained on generic picture datasets. On the other hand, a CNN-based method extracts important features from the images themselves, like consolidations and opacities. Because of this, CNN can identify minor visual cues linked to pneumonia, offering a more reliable and accurate detection method than manually created features or generic pre-trained models[7]. There's no doubt that this can create heavy damage as well as controversy and chaos. Delayed or inaccurate diagnoses of pneumonia can lead to prolonged illness, complications, and potentially life-threatening outcomes for patients. To solve this problem, a system is being built that uses biomedical image analysis and convolutional neural networks to find traumatic meningeal brain injuries. This system will be able to do this by processing images and pulling out features. Developed systems can even detect the most finely forged images with greater accuracy than before. This paper, however, we used a deep learning-based CNN model which changes the way traumatic meningeal brain injuries are diagnosed and gives more accurate results. In this particular scenario, the implementation of an enhanced system that exhibits a higher level of accuracy in the spotting and classification of traumatic meningeal injury (TMI) via the use of deep learning and the Convolutional Neural Network (CNN) algorithm, accompanied by appropriate modifications and increasing layers, would be very advantageous. The architectural configuration of a deep convolutional neural network is likely to be affected by well-established pre-trained models that we later create in an ensemble model and also some handcrafted feature extraction. To gain accurate performance in the three groups of traumatic meningeal injuries, the model will undergo comprehensive tuning and detection using the provided data.

1.1 Problem Statement

In the field of medical imaging, specifically in detecting traumatic meningeal enhancement, an accurate and efficient diagnosis remains a critical challenge. Presently, diagnosis relies heavily on subjective assessments by physicians, leading to time-consuming processes with the potential for human error and variability among operators. Existing image segmentation methods utilizing machine learning require extensive data to be effective. Detecting traumatic meningeal enhancement (TME) is challenging due to its subtle presentation in imaging studies. TME is often seen as a new biomarker on FLAIR MRI after post-contrast in people who might have a traumatic meningeal brain injury. Roozpeykar et al. (2022) and Davis et al. (2020) emphasized differences and different diagnostic capacities among MRI sequences in TME detection, nevertheless. This is addressed by using CNNs designed especially for brain imaging analysis, which automatically picks up complex patterns from different MRI sequences, such as FLAIR and contrast-enhanced imaging. CNNs can help doctors make better diagnoses and make MRIs more widely used by finding small TME signs more accurately and sensitively, as noted by Schweitzer et al. (2019) and Kim et al. (2014) [13] [22]. Furthermore, Asiri et al. (2023) highlighted the need for enhanced identification of brain tumours, a problem that CNN-based segmentation techniques can help with by enhancing the precision and dependability of identifying complicated lesions [26]. The suggested solution uses CNNs, custom-made feature extraction methods, and deep learning to analyze biomedical images. It aims to improve the accuracy of diagnoses, get around current problems, and provide a more reliable way to find traumatic meningeal enhancement in a variety of brain disorders. Convolutional neural networks (CNNs) are better than both manually extracting features and pre-trained models because they can find complex patterns in raw data without any help. CNNs are very good at complex tasks like finding traumatic meningeal enhancement (TME) because they can extract complex features hierarchically, adapt to different data types, allow end-to-end learning, and fine-tune parameters to fit specific datasets. Their ability to provide advantages for transfer learning and lessen reliance on human-engineered characteristics improves their adaptation to medical imaging datasets. CNN's capacity to understand abstract features gets better as its depth grows, but issues like overfitting and the processing costs of deeper structures need to be carefully balanced to prevent problems. Overall, CNNs are better at correctly identifying complicated patterns within medical imaging data because of their adaptive learning, increasing layers, hierarchical feature extraction, and transfer learning capabilities.

General limitations commonly encountered in traumatic meningeal enhancement (TME) detection research based on common challenges in medical imaging analysis: Firstly, research on TME in medical imaging faces limitations due to the scarcity of annotated datasets, which can hinder the training of robust models and impact the generalizability of findings. Secondly, the complexity of TME patterns, including subtle enhancements or irregular shapes, presents challenges for accurate identification and segmentation. Thirdly, the interpretability of neural networks, such as CNNs, can be complex, potentially hindering their adoption in clinical settings where transparency is crucial. Classifying and managing the CNN approaches as computer-intensive is challenging at best. A research study was conducted utilizing a VGG16 deep neural network in an attempt to overcome the challenge of binary classification. An increased demand for computing power corresponds to a more intricate architecture that aims to deliver optimal performance. Only a structure composed of a complex deep neural network can generate enhanced results. The precision of traumatic meningeal enhancement detection is enhanced by the new customized CNN from multiple perspectives; however, a number of the utilized datasets are inconsistent and of poor quality. It is critical to employ a complex deep neural network architecture in the field of traumatic meningeal enhancement detection to achieve better outcomes. This methodology permits the identification of subtle features in biomedical images with greater precision.

1.2 Research Motivation

As the medical sector continues to advance at an impressive rate, the notion of computer-based clinical decision support has emerged as a prominent issue in a study to improve the quality of decision-making in medicine and healthcare. AI can improve personalized treatment by assisting with diagnosis and therapy decisions. As a result, our motivation for this research is to discover a way to understand how AI applications accelerated the diagnosis of traumatic meningeal enhancement and to produce a solution that relies on data accuracy for enhanced decision-making. Our inspiration is to provide a system that will aid healthcare experts in making an effective and enhanced diagnosis by combining image processing principles with Convolutional Neural Network models.
Our motivations for this research are:

1 Recognise image processing and understand its functioning.

2 Analyze pre-processing methods for data, such as augmentation and reshaping.

3 Develop a model to use MRI images to identify traumatic meningeal enhancement.

4 Comprehend how deep learning improves our model.

5 Assist neurologists in identifying diseases more quickly and precisely by offering advice and assistance.

1.3 Research objective

The main purpose of our research is to implement a disease detection method that we have created to detect traumatic meningeal enhancements and classify them as normal, early (pre), or acute (post). To identify traumatic meningeal enhancement, our research integrates the transfer learning technique with a convolutional neural network (CNN). Our proposed CNN model is one of the key elements of the Neural Network; it classifies normal, early (pre), and acute (post) conditions and detects traumatic meningeal enhancements via image detection and classification. Traumatic Meningeal Enhancement (TME) detection represents a critical challenge in neuroimaging due to its subtle and multifaceted nature. Failure to accurately identify TME can hinder timely interventions and appropriate patient care, potentially leading to adverse outcomes. Presently, the identification of TME heavily relies on manual assessment by radiologists or neurologists, a process susceptible to drawbacks such as time inefficiency, subjectivity, and variations influenced by the expertise of the practitioner. These limitations underscore the urgent need for an automated, objective, and precise method to detect TME, emphasizing the pivotal role of advanced technologies in revolutionizing the diagnostic landscape. Leveraging deep learning-based biomedical image analysis and handcrafted feature extraction, this research aims to mitigate these limitations by introducing a novel approach to TME detection. By automating this process and reducing reliance on subjective human interpretation, this methodology seeks to enhance the accuracy and speed of TME identification, thereby significantly improving clinical decision-making and patient outcomes in cases of traumatic brain injury. In recent times, researchers have been doing various types of surveys to identify the severity factors, epidemic level, ages of occurrence, etc. to become aware of this disease. Images from an MRI will be sent into this system. Deep learning will be applied to identify the current condition of the images in terms of disease. After all of the necessary pre-processing, the images are sent through the proposed CNN model, which classifies them into three groups.

1.4 Thesis Organization

In our paper, the first chapter discusses the problems we have encountered while working on our research. These have motivated us to work on the problems and contribute to providing a better outcome. In the following chapter, we have studied the methods and the type of data used, as well as the accuracy rate. From their study, it's easy for us to acknowledge different methods and various models for working on our dataset. In the next chapter, we discussed how custom CNN models have been made and how we tuned to get the maximum accuracy. We have also discussed how we used many pre-trained models and ensemble models. The use of handcrafted feature extraction has also been discussed in this chapter. The following chapter discusses the performances of the models we have used and compares their performances. In our final chapter, we showed our urge how to work in future regarding the current work we have worked on.

Chapter 2

Related Work

2.1 Literature Review

As per Davis, an individual undergoing contrast-enhanced magnetic resonance imaging (MRI) who is suspected of having suffered a traumatic brain injury (TBI) may exhibit traumatic meningeal enhancement (TME), a novel biomarker that can be identified on post-contrast fluid-attenuated inversion recovery (FLAIR). Even in cases when further trauma-related brain abnormalities do not exist, TME may nevertheless be seen on an acute MRI. The study looked at TME's visibility on T1 weighted imaging (T1WI) post-contrast and FLAIR post-contrast and found that 62% of positive FLAIR occurrences were also visible on T1WI at that time. However, in 38% of the instances, TME was positively tested on FLAIR in addition to being negative on T1WI. TME features were examined during a one-year period in 47 people who were suspected to have suffered from traumatic brain injury. In contrast, conflicts were more common than agreement on T1WI. TME on FLAIR revealed almost 100% agreement. In identifying the presence or absence of TME, FLAIR post-contrast MRI performed better than the T1WI post-contrast sequence. When FLAIR post-contrast MRI is used instead of T1WI post-contrast MRI, the results are more consistent overall and interrater agreement. This work highlights the value of FLAIR post-contrast MRI as a useful supplementary imaging modality for clinical TBI imaging procedures in the detection of TME in TBI patients [13].
Roozpeykar et al. described for meningeal lesions, magnetic resonance imaging (MRI) is a commonly utilized diagnostic modality. T1-W and FLAIR sequence diagnostic values are compared following contrast injection in this study. 42.9% of the 147 individuals in the research had a tumoral etiology, and 57.1% had an infectious cause for their meningeal lesions on brain MRIs. FLAIR sequences were able to diagnose 82 patients (97.6%) with meningitis, but T1-W pictures without contrast were only able to diagnose 78 instances (92.8%). For the diagnosis of brain inflammatory disorders, FLAIR sequences exhibited 92% sensitivity and 85% specificity, whereas T1 sequences had 82% sensitivity and 73% specificity. According to the study's findings, FLAIR sequences are superior to T1 sequences in the diagnosis of inflammatory brain disorders. The study also looked at how well FLAIR and weighted-T1 sequences worked in meningeal lesions. It was found that weighted-T1 worked better in lesions that were not infected, but FLAIR sequences worked better in lesions that were. To further corroborate the findings, the paper suggests doing multicentric studies. Infection was better, and tumoral lesions were worse with the

FLAIR sequence. While the contrast-enhanced T1-W sequence is more enhanced in tumoral lesions, overall, contrast-enhanced FLAIR sequences are useful in the early identification of meningeal infections [22].

In the research paper(Schweitzer et al., 2019), The Glasgow Coma Scale (GCS) and the American Academy of Neurology Concussion Guidelines for Traumatic Brain Injury (TBI) were looked at in terms of their strengths, weaknesses, clinical value, and link to outcomes. By emphasizing the use of nonenhanced head CT scans for quick evaluation and directing urgent neurosurgical procedures, it sought to improve TBI therapy and prognostication. While sensitive enough for triage, MRI is particularly good at identifying axonal injuries, brainstem injuries, and nonhemorrhagic contusions. However, owing to expense, longer imaging durations, and safety concerns, its wider usage is restricted. While promising, advanced imaging methods such as diffusion-tensor imaging (DTI) still encounter difficulties with interpretation and standardisation. In exploring a variety of TBIs, such as axonal injuries, developing contusions, and skull fractures, the research places a focus on monitoring and intervention—particularly in older people after falls. It also covers subsequent brain injuries from herniation and vascular damage after severe accidents. In severe cases needing neurosurgical intervention, radiologists advocate for CT scans and play a crucial role in detecting TBI consequences. It also emphasized DTI as a research instrument for TBI evaluation [12].

Kim et al. stated that contrast-enhanced fluid-attenuated inversion recovery (FLAIR) sequences in regular MRI may assist in identifying traumatic brain lesions and other abnormalities not discovered on standard unenhanced MRI, according to research on 54 patients with persisting symptoms after a moderate closed head injury. (Kim et al., 2014) According to the research, contrast-enhanced FLAIR images revealed three more instances of brain abnormalities in addition to the 25 patients who had traumatic brain lesions identified. Nine instances had meningeal enhancement found, but no traumatic brain damage was detected in other routine imaging sequences. In 37 instances, the extra-contrast-enhanced FLAIR pictures showed more widespread abnormalities than regular imaging. It was found that meningeal enhancement on contrast-enhanced FLAIR images could be used to find extra abnormalities and traumatic brain lesions that regular MRI scans don't pick up. The results may enhance patient care for brain injuries and enhance their quality of life. Along with the idea of a subdural space, this study also looks at how intradural computed tomography appearance can help predict traumatic subdural hematomas [3].

Chiara Ricciardi and his team described that in patients with suspected mild traumatic brain injuries, a quick MRI approach was evaluated to identify acute brain damage. In a blinded group of mTBI patients, the methodology distinguished between acute trauma and nonspecific chronic illness, as well as trauma-related abnormalities not seen on CT. An increasing amount of research indicates that in individuals with moderate traumatic brain injury (mTBI), modest structural damage to the brain may go unnoticed on CT. It has been suggested that MRI is a more sensitive modality for identifying minute changes in parenchyma after axonal injury-related trauma. Acute MRI may be able to identify a subgroup of individuals who are more likely to have chronic dysfunction, which might assist in direct early educational intervention and better follow-up treatment. Within 48 hours of their injuries, 24 patients with severe head trauma were prospectively included in the research to get MRI scans. The primary end measure was the presence of

any acute trauma-related brain injury seen on an MRI. The study discovered that MRI findings were consistent with a final diagnosis of mTBI in 54% of patients with suspected mTBI and 85% of the group with suspected mild stroke. The therapy was well-received by all patients and helped distinguish between traumatic and nontraumatic brain abnormalities [5].
Meningitis is becoming more widespread globally, requiring for a more rapid and efficient diagnosis and course of treatment. For leptomeningeal disease, the delayed contrast-enhanced FLAIR MR imaging sequence is more sensitive than contrast-enhanced T1-weighted images. By comparing the MRI and CSF analysis data, one may determine the diagnostic accuracy of delayed gadolinium-enhanced FLAIR MR imaging. Post-contrast MRI can be used to reliably detect infectious meningitis, particularly when combined with delayed post-contrast FLAIR images. In certain instances, this diagnosis can be made even before the CSF is generated. Enough differentiation for the MR imaging characteristics of infectious meningitis to help identify the cause is provided by the anatomical distribution and enhancing features of post-contrast meningeal enhancement. The 2018 strategy plan "Defeating Meningitis by 2030" emphasizes the need for early diagnosis and treatment, as well as timely pathology and causative aetiology identification. Because it is more sensitive to leptomeningeal disorders than contrast-enhanced T1-weighted pictures, some believe that magnetic resonance imaging (MRI) is an effective weapon in the battle against meningitis. To evaluate the diagnostic accuracy of MRI findings for infectious meningitis, this study will compare CSF analysis with MRI data. The study demonstrated that leptomeningeal enhancement may be more accurately detected using post-contrast delayed FLAIR MRI in individuals with meningitis, utilizing a 1.5 Tesla MRI. Differential patterns of enhancement amongst meningitis kinds facilitated accurate etiological diagnosis [16].
Despite the absence of a negative head CT scan, meningeal enhancement may be visible on contrast-enhanced MRI in patients with severe traumatic brain injury (TBI). A gadolinium-based contrast agent brightens the dura and seeps into the subarachnoid space within minutes after entering the blood vessels. The primary objective of the study was to characterize the slow motion of contrast enhancement in the subarachnoid space and the rate of contrast agent uptake in hyperacute individuals following an injury. Pathogenic features of TBI and stroke include the disruption of the blood-brain barrier. Gadolinium is an albumin-binding drug that can cause hyperintense acute reperfusion markers (HARM) in both ischemic and hemorrhagic strokes. This is because it can't get through the blood-brain barrier when it's intact. The first observation of this phenomenon in stroke patients suggests that the process of intravascular contrast leaking from blood vessels into the subarachnoid space is slow. According to the research, 72% of individuals who had both a traumatic brain injury (TBI) and subarachnoid space enhancement (TME) tested positive for TME. In one person with a moderate traumatic brain injury. This made the subarachnoid space bigger. This shows that the blood-cerebrospinal fluid barrier and/or the blood-brain barrier were broken. Peak enhancement that appears six minutes after contrast suggests that TME is a unique biomarker for recent TBI that is not seen in traditional imaging. This 3T MRI study of 102 TBI patients found rapid meningeal enhancement correlations with neurological symptoms. This was true even though follow-up ECSAS scans had problems that suggested the reported prevalence may have been higher than it was. The identification of TBI subgroups

may be improved by using imaging and blood indicators, which are important for comprehending enduring symptoms and neurodegenerative hazards. The research validates that TME may be identified using an MRI procedure brief enough for an acute clinical population in patients with traumatic brain injury. The research focused on meningeal enhancement prevalence post-TBI rather than measuring its diagnostic precision against a gold standard or sensitivity or specificity values. It also examined meningeal enhancement prevalence but did not give accuracy measures [17].

Asiri and his team stated that a major global health problem, brain tumors impacts millions of people. For therapy to be effective and for patients' quality of life to be enhanced, early diagnosis is essential. To effectively detect brain tumors in input data pictures, FT-ViT, a computer-aided vision transformer model, employs deep learning approaches and sophisticated image processing. After being trained on 5712 brain tumor pictures from the CE-MRI dataset, the model's accuracy was 98.13%. Some studies have suggested deep CNN architectures, including FT-ViT, BraTS-Net, and DeepSeg to increase performance. By fusing a CNN with a transformer, the Bitr-unit model improved segmentation performance; nonetheless, real-time application design necessitates certain constraints. Based on the Swin Transformer design, the authors created a new architecture that achieved good segmentation accuracy while being quicker and more memory-efficient for semantic brain tumor segmentation tasks. To detect brain cancers, the researchers analyzed a large dataset of MRI scans and other medical imaging of the brain. The Vision Transformer (ViT) architecture takes MRI scans and pictures as input, breaks them up into patches, flattens each patch into a single long vector, and then uses those patches to make lower-dimensional linear embeddings. In terms of tumor categorization, the model proved reliable; it was also more accurate and time- and money-efficient. The efficacy of the FT-ViT model has the potential to enhance brain tumor identification in the field of medical imaging. Nonetheless, care must be taken to prevent overfitting and guarantee that the model can be applied to complicated or unknown pictures [26].

Lin and his team explained that using the ImageNet dataset, focuses on large-scale picture categorization. Using hundreds of mappers, the researchers created a Hadoop feature extraction strategy that enabled them to extract complex characteristics from 1.2 million photos daily. They also created an approach for training one-against-all 1000-class SVM classifiers using parallel averaging stochastic gradient descent (ASGD). The ASGD method converges quickly, usually in 5 epochs, and can handle terabytes of training data. With 52.9% classification accuracy and a 71.8% top-5 hit rate, the researchers' performance on the ImageNet 1000 class classification was state-of-the-art. The research emphasizes how crucial picture categorization is to computer vision, emphasizing the need for effective feature extraction and classifier training without sacrificing effectiveness. With rapid convergence and parallel computing in mind, the authors suggest a parallel ASGD technique for large-scale ImageNet classification. In contrast to the slower SGD approach, the ASGD method converged rapidly, obtaining a rather decent solution after 5 rounds [2].

Minaee focuses on utilizing a bag-of-word (BoW) technique to identify individuals with mild traumatic brain injury (mTBI) using MRI data. Using the BoW approach, researchers extract several patches from three different brain areas and depict each individual as a histogram of typical patterns. They choose a subset of features

that yields the best accuracy via greedy forward feature selection. According to the research, BoW features outperform straightforward mean value features and provide a strong method for combining local data to create a global representation. The suggested approach is especially helpful for high-dimensional input data collections with small sample sizes. Using a variety of imaging measurements for the Corpus Callosum and Thalamus, the researchers employed the BoW technique, learning 20 visual words from 16x16 patches for each group independently. This method works especially well for high-dimensional input data datasets with small sample sizes. The research included 40 healthy and sex-matched controls, as well as 69 mTBI cases aged 18–64. By using a 5-fold cross-validation methodology, the research assessed the model's performance and increased accuracy to 91%. The suggested approach's sensitivity and specificity were also assessed in the research; these factors are crucial for the analysis of medical data [6].
Another study combines two powerful classifiers, eXtreme Gradient Boosting (XGBoost) and Convolutional Neural Network (CNN), to offer a novel method for photo categorization. The CNN-XGBoost model is an improved version of tree boosting for image classification that makes use of XGBoost to train a tree model additively while increasing speed and accuracy. After normalizing the input picture data and moving it to the CNN's input layer, the model uses trainable features from the CNN training. The trials were conducted on the MNIST and CIFAR-10 databases, and the outcomes showed that the CNN-XGBoost model performed better than other methods on the same datasets. The study suggests that increasing the number of iterations in the CNN optimization process and the hardware operating parameters may improve classification accuracy. The CNN-XGBoost model attained an accuracy of 80.77% on the CIFAR-10 color picture database and 99.22% on the MNIST handwritten digit database. These results demonstrated higher accuracy rates when compared to other models, especially when it came to outperforming other methods on the MNIST dataset. Probably by combining the precise classification of XGBoost with the effective feature extraction of CNN, the CNN-XGBoost model's accuracy was raised. Its optimized design and parameter selections likely outperformed other methods in picture classification on these datasets. The study suggests that further effort be put into optimizing algorithms to speed up the convergence of the cost function and fine-tuning the CNN structure to extract higher-quality features [8].
According to this study by Laukamp and his colleagues, utilizing conventional multiparametric MRI data and a multiparametric deep-learning model (DLM), it was shown that the DLM successfully detected meningiomas in 55 out of 56 cases. The correlation between automatic and manual segmentation was found to be high. In T1CE, the average Dice coefficients were 0.81 ± 0.10 for the overall tumor volume and 0.78 ± 0.19 for the contrast-enhancing tumor volume. This suggests that deep learning might improve the detection and classification of meningiomas, aiding doctors in patient evaluation and possibly improving treatment regimens and oversight. The study suggests that automated meningioma segmentation and identification might improve image interpretation and allow for more in-depth tumor volume analysis. The study aimed to tackle problems such as anatomical variations, conflicting imaging data from different scanners, and variations in scanner settings. The automated detection and segmentation of meningiomas based on a deep learning model was demonstrated to be accurate and reliable even with variable MR data from various scanners [11].

This research aims to develop an automated approach for brain MR image classification, enabling radiologists and other medical professionals to automatically diagnose brain tumours. The system uses convolutional neural networks (CNN) and deep learning techniques to classify the brain MR images into four categories: normal brain, pituitary tumour, meningioma tumour, glioma tumour, and tumour. For a fair evaluation, the 5712 MR images in the dataset are split into training and validation sets using an 80-20 ratio. After the extracted features are evaluated by several machine-learning classifiers, the three best-performing features are merged to create a powerful feature ensemble. Then, to separate the brain MR images into four groups—normal brain, meningioma tumour, glioma tumour, and pituitary tumor—the Ensemble is coupled with the Multilayer Perceptron classifier. The results of the experiments indicate that the MLP classifier's performance significantly changes when features from ResNet-50, VGG-19, and EfficientNetV2B1 are combined using the Features Ensemble approach. A remarkable accuracy of 96.67% with a 95% confidence level was obtained as a consequence. This method shows how effectively it can categorise brain MR pictures and how it may be used to improve diagnostic abilities, outperforming existing state-of-the-art methodologies [29].
In 2014, there were 56,800 documented cases of traumatic brain injury (TBI) deaths. Brain trauma is a leading cause of death and disability. Early detection has the potential to reduce ER visits and save lives. Previous methods involve the use of mobile health applications that need expensive and time-consuming clinical testing, such as CT scans. More and more sensor-rich smartphones are emerging as a useful platform for continuous health monitoring. This work explores the identification of traumatic brain injury (TBI) early in the damage process using gait, balance, and mobility patterns in smartphone sensors. We compared and investigated three machine learning processes: computing hand-crafted features on raw sensor data and encoding raw mobility patterns using an auto-encoder-based technique. The study analyzed six location metrics, nine gaits, and four balancing statistical features derived from accelerometer sensors and smartphone location data using different segmentation algorithms. Machine learning techniques were used to classify and normalize these attributes. The greatest results were obtained when gait, balance, and mobility variables that were manually developed were classified using tree-based classifiers. With a 24-hour window size and manually designed feature extraction, the best outcomes were achieved with XGBoost on the third day following injury [19].
This work proposes a computer vision-based approach for automatically identifying brain disorders. The model consists of four stages: preprocessing, creating example deep features, choosing features using iterative neighborhood component analysis (INCA), and classifying the results using support vector machines (SVM). The model is based on MobilNetV2, an exemplar-based deep feature generator. An MR imaging dataset of 444 pictures with three distinct illness categories and control groups was used to evaluate the model. The model's SVM classification accuracy was 99.10%. Preprocessing, using MobileNetV2 to generate exemplar features, selecting features using INCA, and classification are the four primary phases of the model. Patches $128 \times 128 \times 3$ and $256 \times 256 \times 3$ are used in the model. This study shows how well the suggested approach works in identifying brain disorders from MRI pictures, an essential diagnostic and therapeutic tool in medicine. Although several techniques for classifying brain MRI images have been studied, machine learning-based models

are necessary for precise diagnosis. This work uses preprocessing, including deep feature extraction, feature selection, and classification, to examine a dynamic-size patch-based deep feature generation model's ability to classify images. When used in conjunction with different learning models, the parametric model may be beneficial for medical picture categorization. The study highlights how important machine learning-based models are in identifying brain disorders since incorrect diagnosis may result in both morbidity and mortality [21].

Classifying brain tumours is essential for computer-assisted diagnostic (CAD) assessment of medical conditions. Using an MRI for manual diagnosis might be time-consuming and result in inaccurate identification. Convolutional Neural Networks (CNNs), one type of Deep Learning technology, have made medical image processing more automated. This work presents a novel CNN technique for the categorization of pituitary, glioma, and meningioma brain tumours. The algorithm acquired a high precision, recall, f1-score success rate of 98%, and classification accuracy of 98.04%. Their proposed model fared better than InceptionV3, which had the lowest accuracy rates of 85.77%, 86% for precision, 84% for recall, and 85% for f1-score. Its accuracy rate was 98.04%, while its rates for precision, recall, and f1-score were all 98%. It is noteworthy that their results corroborate the idea that the low performance of InceptionV3 is caused by the excessive usage of concurrent convolutional and pooling layers, which are inappropriate for tiny datasets [28].

To detect potentially lethal abnormal tissues and to provide medication that effectively aids in the patient's recovery, it is imperative to classify brain tumours. Due to their higher image quality and non-ionizing radiation, medical imaging methods such as magnetic resonance imaging (MRI) are widely employed. Artificial intelligence's deep learning field has greatly enhanced the process from MRI to better prediction rates for brain tumour detection. Convolutional neural networks (CNNs) are the most complete and widely used deep learning method for the investigation and categorization of brain tumours. This study examines the independence of brain tumor cell detection using CNN-pretrained models based on transfer learning, such as VGG-16, Inception-v3, and ResNet-50. The study looks at how epoch numbers affect sickness prediction and how well these algorithms are in classifying data overall. The dataset consisted of a subset of brain MRI pictures taken from the Kaggle dataset. The transfer learning approach uses pre-trained models that are already accessible and have been trained on a large dataset, such as ImageNet, for image classification, as opposed to building the CNN detection model from scratch. The focus of the work is on employing pre-trained CNN architectures for the classification of MRI brain tumour images. The models are applied to a dataset of 253 brain MRI images. The confusion matrix results show that although the VGG-16 model has a poor accuracy rate, it matches the MRI dataset very well. Every design attains training accuracy of more than 0.9000%, with the greatest validation accuracy of 0.8826%. The proposed study might be extended to classify brain tumours using other CNN-based models that have already been trained [23].

According to the evaluation in this article, 205 individuals had a regrettable death rate of 55.7%. Nonsurvivors had a higher Injury Severity Score (ISS) of 25 vs. 16 ($P < 0.001$) and a lower GCS of 5 vs. 7. Platelets, haemoglobin, and albumin levels were significantly lower in nonsurvivors, although their levels of glucose and prothrombin time were significantly larger in survivors ($P < 0.001$) and $P < 0.001$, respectively. The most significant parameters in the XGBoost approach were glucose, prothrombin time, and GCS. In comparison to logistic regression, XGBoost performed better in terms of accuracy (0.955 vs. 0.70) and area under the receiver operating characteristic curve (0.955 vs. 0.805). In terms of forecasting the death of patients with moderate-to-severe traumatic brain injuries, their research showed that the XGBoost algorithm outperformed conventional logistic regression. Several machine learning methods, including as support vector machines, decision trees, random forests, Naive Bayes, and artificial neural networks, have also been examined in earlier research in relation to the prognostic values of the patients. In terms of forecasting patients' mortality from moderate-to-severe traumatic brain injury (TBI), this study indicated that the XGBoost technique performs better than logistic regression [24].

While there has been progress in the field, algorithms for recognising images of acute traumatic brain injury (TBI) still have difficulties in detecting important anomalies such as edema, fractures, infarcts, and mass effects. Complex image data is difficult for traditional machine learning algorithms to correctly handle. Convolutional Neural Networks (CNNs), one of the deep learning algorithms that have revolutionized image analysis, are capable of learning complex patterns from large amounts of data. The inability to generalize performance across institutions and the absence of standardized datasets for comparison present difficulties, however. These algorithms have the potential to improve TBI imaging and make it more accurate and grounded in facts, even in the face of these obstacles. Data labeling procedures have an impact on model performance and applicability in medical imaging tasks. In the treatment of people who have recently had a stroke, MRI bleeding detection algorithms like those for triage, localization, skull fracture, intracranial mass effect, and stroke identification may help doctors make more accurate predictions about the patient's prognosis and more personalized treatment plans [10].

To help in the detection of traumatic brain injuries, a new collection of CT images has been developed (TBI). It is predicated on a unique imaging diagnostic model comprising an integrated squeeze-and-excitation module, recurrent neural networks (RNN), and convolutional neural networks (CNN). With an accuracy of 95.9%, the model exceeds other popular classification networks when it comes to slice-level damage prediction. The mortality and disability rate from traumatic brain injury (TBI) is very high. Traditional machine learning-based approaches are slower and have technical difficulties, but deep learning-based techniques have gained favour because of their accuracy and speed. To automatically diagnose TBI, this study proposes a unique architecture that blends CNN and RNN with attention processes. The approach first uses an SE module to get the fundamental image characteristics, and then it employs an RNN network for slice-level TBI classification tasks. With a sensitivity of 0.933, specificity of 0.989, and accuracy of 0.959, the classification results are outstanding and beat the current dominating architecture. The study concludes that the proposed method successfully detects traumatic brain injury (TBI) in brain CT images and may be used for other brain injury categorization tasks [15].

A fully convolutional neural network (CNN) model can find lesions and contusions in brain magnetic resonance (MR). The CNN architecture segments lesions from multi-contrast MR images using a 3-layer Inception network, which is based on Google's Inception design. On photos of eighteen individuals with moderate to severe traumatic brain injuries, the suggested approach demonstrated better segmentation accuracy. The model outperformed two rival approaches, achieving a mean Dice of 0.75 with the use of a leave-one-out cross-validation. Mini-batch sets of patch triplets from several atlases were used as the training input, and each patch's centre voxel had a non-zero label based on hand segmentations. Due to the elimination of completely linked layers and larger patch sizes, the suggested strategy resulted in reduced false positives and more accurate segmentation. Upcoming research will concentrate on maximizing patch depth and size, contrasting with whole 3D patches, and identifying various kinds of lesions. In particular, the research investigates the use of deep convolutional networks for brain MRI segmentation in traumatic brain injury scenarios [9].

Chapter 3

Methodology

In this study, our focus revolves around the utilization of deep learning techniques and hand-crafted feature extraction methods to detect traumatic meningeal enhancement (TME) within biomedical images. Leveraging the dataset obtained from the seminal work by Davis et al.[13] It used contrast-enhanced magnetic resonance imaging (MRI) to thoroughly investigate the occurrence of TME in patients with suspected traumatic brain injury (TBI), to create an advanced algorithm. By harnessing deep learning architectures, we intend to train models capable of identifying subtle yet crucial features indicative of TME within these images. Additionally, our approach involves extracting hand-crafted features, allowing for a hybrid methodology that combines the power of learned representations with domain-specific features. The integration of deep learning-based biomedical image analysis and handcrafted feature extraction is poised to significantly enhance the accuracy and efficiency of TME detection, offering a promising avenue for advanced diagnostic applications in TBI assessment.

The process comprises of a traditional CNN model with a 13-layered architecture and a transfer learning technique that leverages four pre-trained CNN models (InceptionV3, VGG16, VGG19, and MobileNetV2) for training the data set and refine and ensemble it for comparison. We also used custom feature extraction methods like Histogram of Oriented Gradients (HOG), Mean Pixel Value (MPV), and Positional Orientation (PO). These were then used to train models like Support Vector Machine (SVM) and XGBoost and compare their performance to CNN models based on deep learning. Standard assessment measures, including accuracy, precision, recall, and F1-score, were used to evaluate each model's performance. Based on the handcrafted features retrieved by SVM and XGBoost, the customized CNN model performed better than the pre-trained models. The study concludes by emphasizing the significance of deep learning-based approaches in biomedical image analysis for TME detection. The phases which make up the procedure have been broken down and given below in an organized way.

- Step 1: Data Collection
- Step 2: Data Augmentation
- Step 3: Custom CNN model
- Step 4: Existing pre-trained models
- Step 5: Ensemble pre-trained models

- Step 6: Feature extraction
- Step 7: Handcrafted model
- Step 8: Performance Evaluation

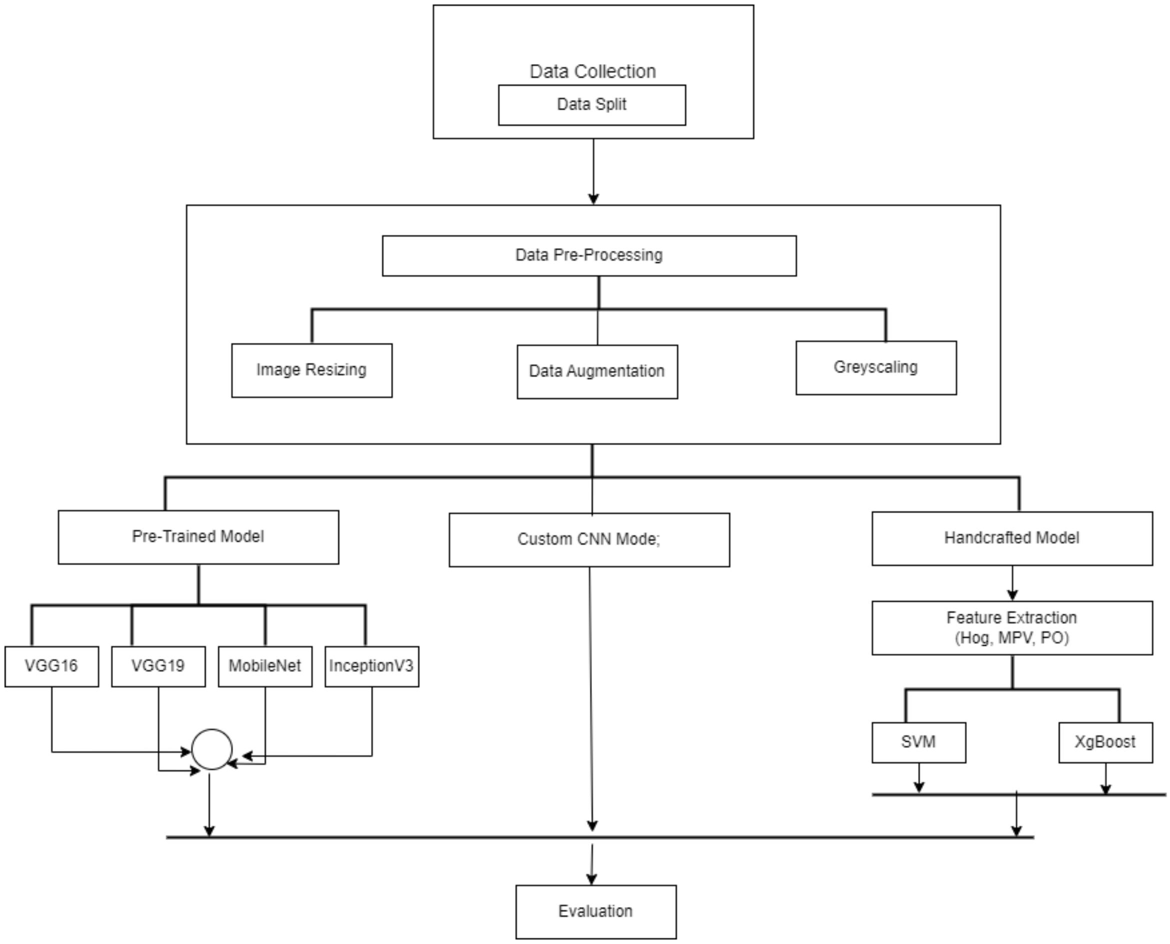

Figure 3.1: Workflow

3.1 Data Collection

We have worked on data from deidentified brain MRI (T1 and FLAIR pre- and post-contrast sequences). The images are in Dicom format [14]. We have collected the data from the NIH Figshare database. Initially, the zip file contained a total data of 4108 images. However, we have shortened and collected a total of data 800 MRI images. After that, we augmented our data for the better performance of our models. We have also collected some normal MRI image data as well [27]. The data were separated into 3 classes named pre(early), post(acute), and normal where the images are divided into training and testing. We have set different resolutions and pixels for working on the data on our models for the best outcomes. Every image is then processed afterward. A visual representation of a few images is shown in the figure.

Figure 3.2: Normal

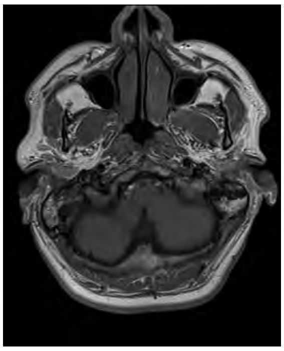

Figure 3.3: Pre (Early)

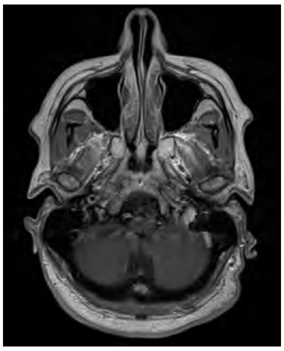

Figure 3.4: Post (Acute)

3.2 Dataset Description

Firstly, the data has been converted from a .dcm to a .jpg file using the Pydicom and Pillow libraries. We split our dataset into two parts. One is the training dataset and another is the testing dataset. In the training part, we used 6000 images and for the testing part, we used 1800 images. We have demonstrated our sample of dataset and the data splitting pie-chart sequentially.

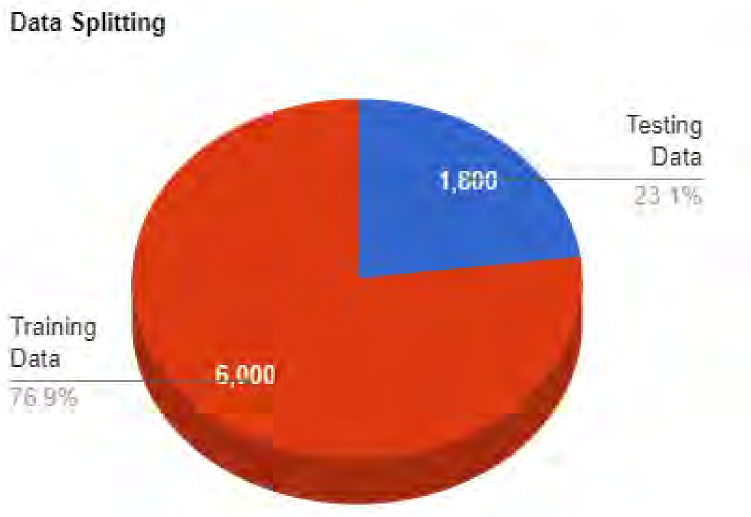

Figure 3.5: Data Splitting

3.3 Dataset Pre-Processing

One of the challenging phases is the retrieval of information from data. The aim of data pre-processing is the minimization of inconsistent data. It also helps to reform inadequate inputs. What we see from our final training and testing sets is the result of data pre-processing. Pre-processing can be done through various methods. Like filtering, normalization, modification, feature extraction, etc. Among the methods that we know, we chose resizing, augmentation, and feature extraction for pre-processing our dataset. As we know, we have very limited numbers of data and there might be a chance that the accuracy that we expect from the models might not be the one as we expected so this method is very important for us. In our dataset, one of the major features that has to be processed for models to perform well is the image conversion technique. The detailed descriptions are stated below:

- **Image conversion:** The raw data that we collected were on DICOM file. We imported the Pydicom, os, and PIL modules to handle the operation. We then set the folder for DICOM and JPG images. Upon the loop, it then reads the DICOM file and extracts the pixel array. After that, it rescales and converts the pixel values to fit within the range 0-255 and uint8 datatype. In the end, it creates a PIL image from the pixel array and saves it in the output folder.

- **Resizing Images:** We have tried to keep our focus on sequential models like CNN which is why we scaled our images as per the requirements of our models. We have kept the resolution size of 128x128 pixels for the transfer learning approaches. We know, CNN can take only the fixed dimensions, it's a necessity for us to resize it. We also resized the data for our 13-layer sequential model.

- **Image Augmentation:** The use of this method was important increasing the amount of data for maximizing our training data. We tried to reshape, rescale, shear, zoom, right shift, left shift, width shift, height shift, vertical flip, and horizontal flip for all the classes. These are the different augmentation methods that we used. These are mainly used in training the dataset but they will be included in the evaluation.

3.4 Architecture of Proposed Model

We used the Keras neural network toolbox to build a sequential CNN model for the given system. The correctness of the model was examined. Thirteen layers make up the model. Additionally, there were three max max-pooling layers, three 2D convolutional layers, and an equal number of batch normalization layers. Two layers of dense paint, then one layer of flattening and a dropout layer.

- **Input Layer:** This is the first convolutional layer, and it uses the Rectified Linear Unit (ReLU) activation function with 32 filters of size (3, 3). The input shape is supplied as (img height, img width, 3), giving the input images' height, width, and colour channels

- **Pooling and Normalization Layers:** The code repeats a similar pattern twice for additional convolutional blocks. The second convolutional block uses 32 filters, and the third one uses 64 filters. Each block is followed by max pooling and batch normalization.

- **Flatten Layer:** This layer flattens the output from the preceding convolutional blocks, transforming it into a one-dimensional vector. It provides the data for the completely interconnected layers.

- **Fully Connected Layers:** The fully linked layer features ReLU activation function and 256 neurons. With a rate of 0.5 for dropout, half of the neurons in this layer will be arbitrarily set to zero at each update during training. This aids in avoiding overfitting. Three neurons in the last layer, which represents the three classes in the classification job, are part of a densely linked output layer. The probability distributions over the classes are obtained using the softmax activation function.

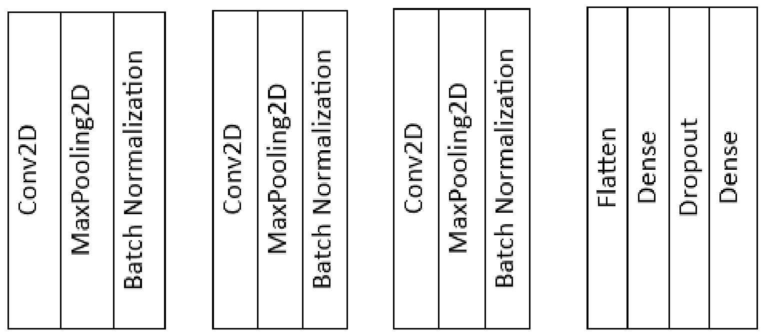

Figure 3.6: Architecture of 13-Layer CNN Model

Table 3.1: 13-Layer Custom CNN Model

Layers	**Output Shape**	**Parameter**
conv2d (Conv2D)	(None, 126, 126, 32)	896
max_pooling2d (MaxPooling2D)	(None, 63, 63, 32)	0
conv2d_1 (Conv2D)	(None, 61, 61, 32)	9248
max_pooling2d_1 (MaxPooling2D)	(None, 30, 30, 32)	0
conv2d_2 (Conv2D)	(None, 28, 28, 64)	18496
max_pooling2d_2 (MaxPooling2D)	(None, 14, 14, 64)	0
flatten (Flatten)	(None, 12544)	0
dense (Dense)	(None, 256)	3211520
dropout (Dropout)	(None, 256)	0
dense_1 (Dense)	(None, 3)	771

3.5 Architecture of Pre-trained Model

In models that have been trained, the neural network was previously used earlier and has learned information that can be employed in new samples that were specially picked. Four models that have already been trained were employed in the test. They are VGG-16, VGG-19, Inception V3, and MobileNet. Here are the specifics of each model:

VGG-16: VGG16 is widely regarded as one of the greatest vision model architectures ever developed. True to its name, it's a 16-layer deep neural network. With 138 million parameters, VGG16 is a vast network even by today's standards, making it relatively enormous. Conversely, the main feature that makes the VGGNet16 design appealing is how simple it is. An RGB picture with 128x128 dimensions must be supplied to the VGG model. For every picture in the training set, the mean RGB value is calculated and then supplied as input to the VGG convolutional network. The convolution step remains constant and it employs a 3x3 or 1x1 filter [25].

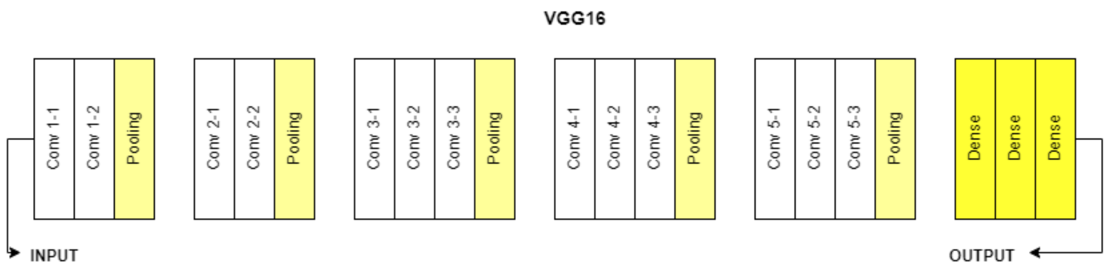

Figure 3.7: Architecture of VGG16 Model

VGG-19: The VGG19 model operates on the same premise as the VGG16 model, with the exception that it supports 19 layers. In VGG19, a fixed-size (128x128) RGB image served as the input, represented as a matrix of shape (128,128, 3). The only preprocessing step involved removing the mean RGB value from each pixel, a process performed across the entire training set. The network employed kernels of size (3 * 3) with a stride size of 1 pixel, ensuring complete coverage of the image. Spatial padding was incorporated to keep the spatial resolution of the input. Max pooling was applied over 2 * 2-pixel windows with a stride of 2, adding to the down-sampling process. After that, Rectified Linear Unit (ReLu) activation functions were used to add non-linearity, which was different from earlier models that used tanh or sigmoid functions. This led to better classification performance and faster computing. The architecture featured three fully connected layers, with the first two layers having 4096 nodes each. Subsequently, a layer with 1000 channels was applied for a 1000-way ILSVRC classification, culminating in a final softmax layer for a probability distribution [20].

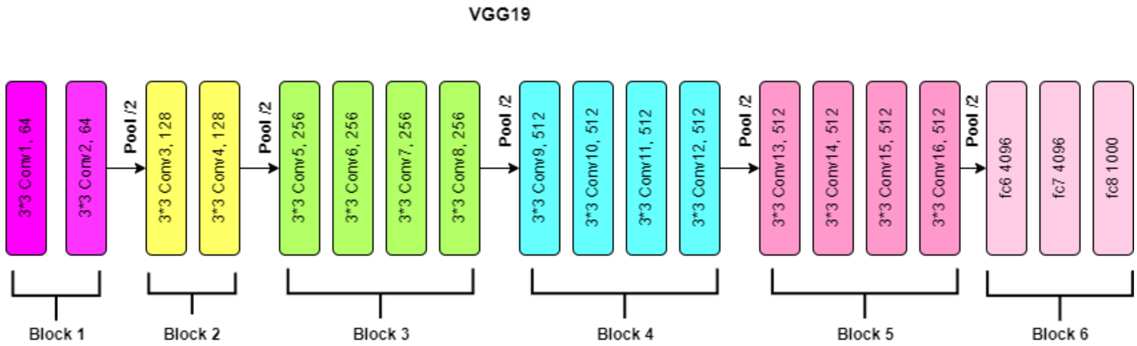

Figure 3.8: Architecture of VGG19 Model

Inception V3: Based on convolutional neural networks, Inception V3 is a deep learning model for categorizing images. The basic model Inception V1, which was made public as GoogLeNet in 2014, has been improved into the Inception V3. The main goal of Inception v3 is to reduce processing power consumption by making changes to the earlier Inception designs. Convolutional neural networks (CNNs) must be used effectively to increase computational efficiency, as the Inception V3 model demonstrates. One important tactic is to decrease a network's parameter count, which boosts performance and quickens the training process. Substituting bigger convolutions with smaller ones not only improves computational processes but also accelerates training. For instance, replacing a 5×5 filter with two 3×3 filters lowers the parameter count from 25 to 18 (33 + 33). Additionally, innovative convolutional strategies, such as replacing a 3×3 convolution with a combination of 1×3 and 3×1 convolutions, add to network optimization. In the Inception V3 model, the introduction of auxiliary classifiers further enhances network depth and works as a useful tool for regularization. In addition, auxiliary classifiers in Inception V3 serve as regularizers, a change from GoogLeNet where they were employed to deepen the network. In terms of grid size reduction for feature maps, Inception V3 takes a break from traditional practices, expanding the activation dimension of network filters instead of depending on max pooling and average pooling. This innovative approach promises an efficient reduction of the grid size while maintaining computational effectiveness in the Inception V3 model [18].

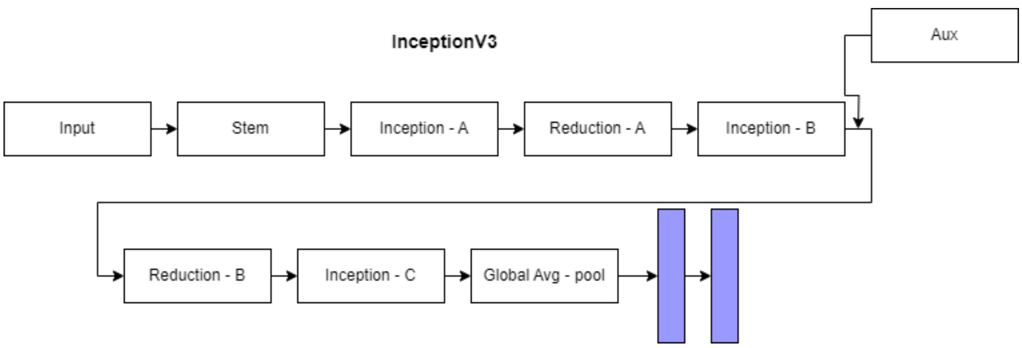

Figure 3.9: Architecture of Inception V3 Model

MobileNet: The MobileNet deep learning model was first presented by Andrew G. Howard. MobileNets uses a simplified architecture to produce effective deep neural networks by using depth-wise separable convolutions. A type of factorized convolution known as depthwise separable convolutions is used by the MobileNet model. A standard convolution is divided into two halves by these convolutions: a depthwise convolution and a 1×1 convolution sometimes referred to as a pointwise convolution. Depthwise convolution, or applying one filter to every input channel, is what MobileNets do. The outputs of the depthwise convolution are mixed by the pointwise convolution using a 1×1 convolution. A total of 27 convolutional layers make up the MobileNet model: 1 fully connected layer, 1 average pooling layer, 1 softmax layer, and 13 depthwise convolution layers. The standard MobileNet model has 4.2 million parameters, whereas the more basic MobileNet models have 1.32 million parameters [30].

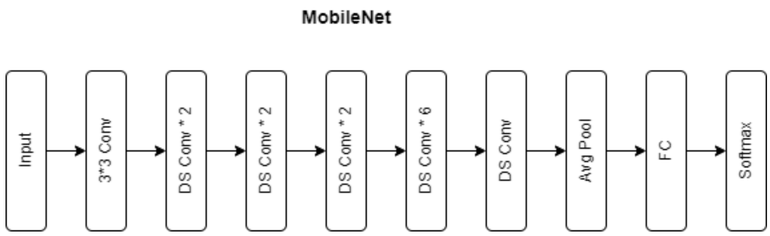

Figure 3.10: Architecture of MobileNet Model

3.6 Architecture of Ensemble Model

To increase performance overall, an ensemble model aggregates predictions from several distinct models. The average of the predictions made by each individual model in an averaging ensemble yields the final forecast for a given input. Here's how to use pre-trained models such as VGG16, VGG19, MobileNet, and InceptionV3 to generate an averaging ensemble. The top (classification) layers are absent from and pre-trained weights are used in the VGG16, VGG19, MobileNet, and InceptionV3 models. One obtains the output tensors derived from the basis models. The element-wise average of the predictions made by each of the various models is determined using the Average layer. The averaged output is produced by the final ensemble model, which starts with the original input. By aggregating and averaging the characteristics that each individual model learns, an ensemble model has the potential to improve overall predictive performance. Before training or predicting, make sure the ensemble model is assembled using the proper optimizer, loss function, and metrics.

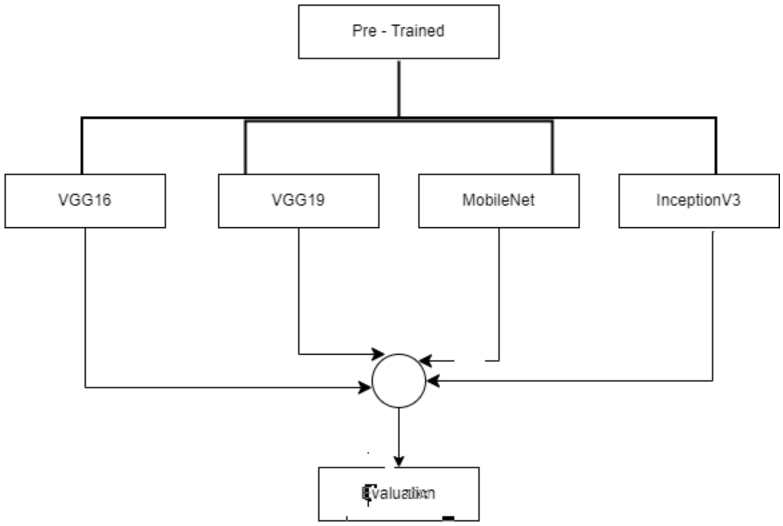

Figure 3.11: Architecture of Ensemble Model

3.7 Architecture of Handcrafted Model

XGBoost: We build an XGboost model by using hog, mpv and po feature extractor algorithms. To construct our model, we take into account the following parameters: gamma, learning rate, max delta step, max depth, min child weight, n estimators, n thread, objective, reg alpha, reg lambda, scale pos weight, quiet, and subsample parameters. Gamma controls the regularization on the tree. A higher value (0.5 in this case) indicates a preference for fewer and deeper splits in the tree, which can help prevent overfitting. The learning rate determines the step size at each iteration. A lower value (0.01 in this case) means smaller steps, leading to a slower but potentially more precise convergence during the training process. This parameter limits the step size during the optimization process to help prevent overfitting. A value of 0.1 implies a relatively small allowed step size. Max depth sets the maximum depth of each tree. With a value of 4, the trees in the ensemble are limited to a moderate depth, capturing intermediate-level feature interactions. It is the minimum sum of instance weight (hessian) needed in a child. A low value like 0.2 allows for fine-tuning of child weights and can help prevent overfitting. This specifies the number of boosting rounds or trees to be built. With only 10 trees, the model is relatively simple, and increasing this value might improve performance. Sets the number of parallel threads used for training. With 4 threads, the training process can leverage parallel processing capabilities. The objective function defines the learning task. 'multi:softmax' indicates a multi-class classification problem, where the model predicts one out of multiple classes. It is the L1 regularization term on weights. A value of 0.5 adds a penalty for having non-zero coefficients, encouraging sparsity in the model. L2 regularization term on weights. A value of 0.8 adds a penalty for large coefficients, helping to control the overall magnitude of the weights. Controls the balance of positive and negative weights, useful for addressing class imbalance. A value of 1 suggests a balanced weight between classes. If False, it prints messages during training, providing information about the training process. t is the fraction of training data to be randomly sampled for each boosting round. A value of 0.8 implies that each tree is trained on 80% of the training data, introducing randomness to improve robustness and prevent overfitting.

SVM: Using the hog, mpv, and po feature extractor algorithms, we construct a Support Vector Classification from Support Vector Machines. We import the model from Sklearn. To observe our model performance, we set some default parameters like kernel, degree, gamma, coef0, shrinking and probability. These parameters allow users to configure the behaviour of the support vector machine based on the characteristics of their dataset and the desired trade-off between model complexity and generalization. The fit method is used to train the model on a given dataset, and the trained model can then be used for making predictions using the prediction method.

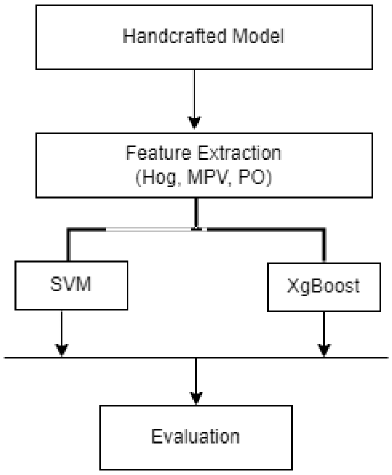

Figure 3.12: Architecture of Handcrafted Model

Chapter 4

Performance Study

4.1 Implementation

The size, epoch, layer, group, transformer layer, plates, trees, callbacks, filter size, and matrix are the parameters that regulate the training dataset for this model in comparison to the proposed network. Validation accuracy, validation loss, training accuracy, and testing accuracy were acquired by the trained and tested models. Training is initiated when the training images have been pre-processed. The max pooling layers in the model's architecture come after the convolutional layers. The pre-trained models and the custom CNN model are selected before the machine learning process begins, and the directory from the three established groups is imported by the required input first layer size. Three phases are utilized to obtain the picture type datatype: early, acute, and normal. Two portions of the data have been extracted: 23.1% for testing and 76.9% for training. 6,000 of the 7,800 images are for training, while the remaining images are for testing. The optimizer used is called "Adam" [10], and it uses a gradient-based strategy centered on creative, simpler time predictions to enhance stochastic objective functions. In cases involving large quantities of data and/or parameter values, the optimizer "Adam" is used because of its simplicity of development, computational performance, minimal memory needs, and invariance to diagonal rescaling of the gradients.[4].

While the second number is used to calculate the percentage contributions from the previous simulation to the current one, the first value is utilised to prevent overfitting. 35 epochs and 32 batches have been used. Before moving on to the next epoch, training and validation data are mixed, which increases the learning process' complexity. Every image has its color mode set to RGB. An activation function called "ReLU" has been employed.The Rectified Linear Unit (ReLU), a non-linear activation function, makes the network more non-linear by letting positive values through but blocking negative ones. This makes it easier for the model to find complex features in biomedical images. "Categorised cross-entropy" is what we employed under the loss part. The categorical cross-entropy loss function makes it easier for the model to tell the difference between different kinds of enhancement in biological images. This is accomplished by calculating the difference between the actual and expected class probabilities. By penalizing deviations from the actual class distribution, this non-linear function forces the neural network to search for the optimal parameters. As a result, multiclass categorization becomes more accurate. The class mode has been set to "categorical" to predict the outcome. By assigning each image to one of numerous enhancement severity groups, this situation provides a thorough categorization of the degree or type of enhancement present in the biological pictures. To mitigate overfitting and improve the network's capacity for generalization, we employed Dropout, a regularisation approach included in the deep learning model. Dropout involves randomly deactivating neurons during training. The output layer uses the softmax activation function to provide probability distributions that help categorize biological pictures into different enhancement classes.Lastly, the color mode section was selected with the "RGB" color option selected, meaning that the photos would be converted to three channels. A graphics processing unit serves as the computational environment for each test (GPU). For benchmarking and informational reasons, Google Colab randomly installed three GPUs: the Geforce Tesla K80, Geforce Tesla T4, and Geforce Tesla P4. To view the GPU's specs, use "!nvidia-smi" in the Google Colab command line..

The training process is examined with reference to the optimizer's repetition as a deep learning technique. In general, the "Adam" optimizer function is described by equation (4.1).

$$\omega_{t+1} = \omega_t - \alpha m_t \tag{4.1}$$

$$m_t = \text{aggregate of gradients at time } t$$

$$\alpha = \text{learning rate at time } t$$

$$\omega_t = \text{weights at time } t$$

$$\omega_{t+1} = \text{weights at time } t+1$$

Positive values are retained, while negative values are converted to zero using the Rectified Linear Unit (ReLU) activation function.

$$f(x) = \max(0, x) \tag{4.2}$$

x represents the input to the ReLU function.
$f(x)$ denotes the output of the ReLU function.
The function $f(x)$ returns x if x is positive or zero; otherwise, it returns zero.

$$L(y_t, y_p) = \sum_{i=1}^{3} y_{t,i} \cdot \log(y_{p,i}) \tag{4.3}$$

y_t is the true label distribution vector in a one-hot encoded form for the three classes.
y_p is the predicted probability distribution vector across all three classes.
$y_{t,i}, y_{p,i}$ represent the true and predicted probabilities for each of the three classes.

Training is initiated by clicking the "model. fit" in the code. Below the contents of the cell is a progress indicator showing the stages and epoch of the entire procedure. The pre-trained model with all of the parameters and matrices selected indicates that the primary validation parameter has been completed when the designated time is completed.

Table 4.1: Parameters Used for the Pre-trained Models and the 13-Layer CNN Model

Parameter	**Pre-trained models**	**13-layered CNN Models**
Train Data	70%	70%
Test Data	30%	30%
Target Size	(128,128)	(128,128)
Batch Size	32	32
Epoch	35	35
Environment of Execution	GPU	GPU
Optimizer	Adam	Adam
Loss Function	Categorical CrossEntropy	Categorical CrossEntropy
Activation Function	Softmax	Softmax
Class Mode	Categorical	Categorical
Colour Mode	RGB	RGB

4.2 Performance Matrices

Here the calculation of accuracy, precision, recall and AUC performance of each model is stated[1]. The equations are described below:

$$\text{Accuracy} = \frac{\text{True Positive} + \text{True Negative}}{\text{Total Correct Predictions}} \tag{4.4}$$

$$\text{Precision} = \frac{\text{True Positive} \times \frac{\text{True Positive Rate}}{\text{True Positive}}}{\text{False Positive}} \tag{4.5}$$

$$\text{Recall} = \frac{\text{True Positive} \times \frac{\text{True Positive Rate}}{\text{True Positive}}}{\text{False Negative}} \tag{4.6}$$

$$\text{F1 score} = \frac{\text{True Positive}}{\text{True Positive} + \frac{1}{2} \cdot (\text{False Positive} + \text{False Negative})} \tag{4.7}$$

AUC: A measure of a classifier's capacity to distinguish between classes is referred to as the Area Under the Curve (AUC) [1]. It just expresses the degree of independence or the scale by which it is assessed. Given that AUC is scale and classification-threshold-invariant, it provides an aggregated performance statistic across all thresholds. How well the model distinguishes between positive and negative categories is shown by the AUC rate. An increased AUC rate indicates improved performance for each specific model.

In the following graphs x - axis defines the number of epochs and y - axis defines accuracy rate.

4.3 Performance of CNN Model

We selected 7800 images among them we used 6000 images for training and 1800 images for testing, separated into three portions for normal brain, early (pre), and acute (post).Each class's training data accounts for 76.9% of the total data, while testing data accounts for 23.1%. Finally, our proposed model was found to be 91% correct.

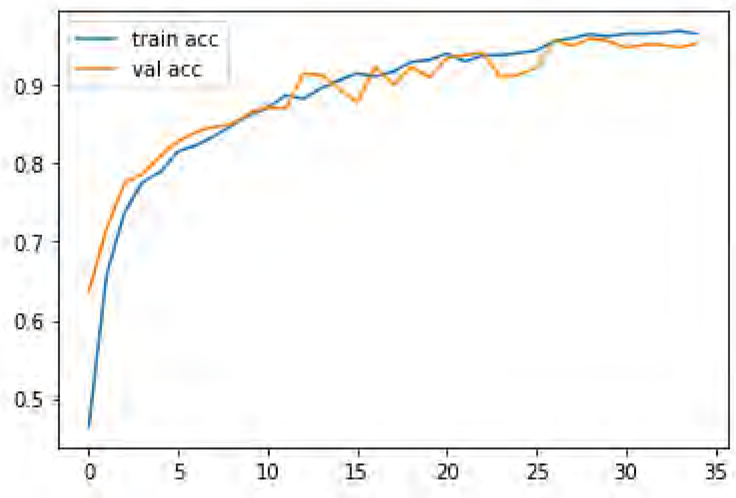

Figure 4.1: Custom CNN Model Accuracy

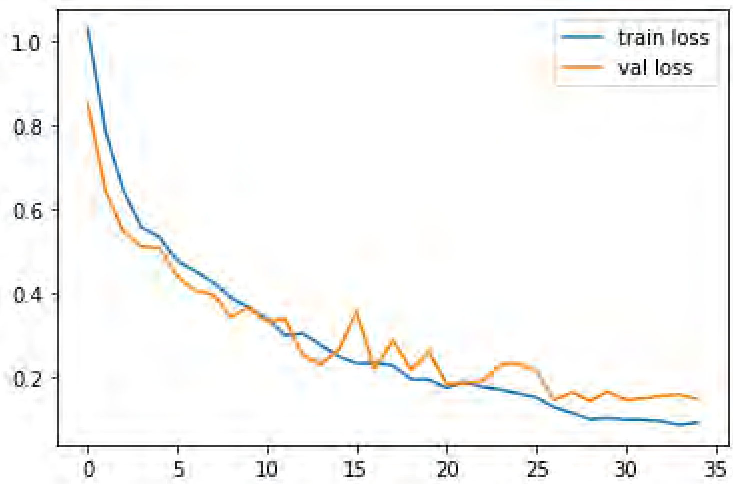

Figure 4.2: Custom CNN Model Loss

	precision	recall	f1-score	support
normal	0.81	0.94	0.87	600
post	0.96	0.71	0.82	600
pre	0.85	0.93	0.89	600
accuracy			0.86	1800
macro avg	0.87	0.86	0.86	1800
weighted avg	0.87	0.86	0.86	1800

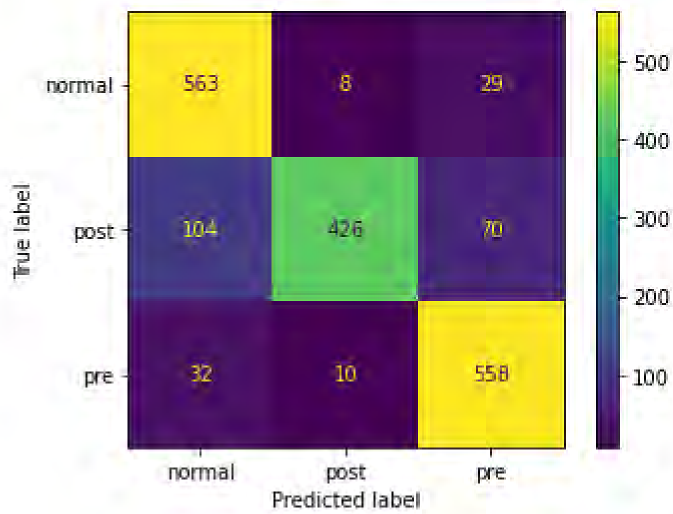

Figure 4.3: Custom CNN Model Confusion Matrix

4.4 Performance of Pre-Trained Models

As we have stated before, the total number of images is 7800, where we have divided our image. 1800 images are used for our testing,, where we have divided these images into 3 segments of 600 for each class. The classes are normal, pre(Early) and post(Acute). We have run these images into different pre-trained models. We have used MobileNet, InceptionV3, Vgg16, and Vgg19. Upon analysis, we have found that MobileNet has performed better than other models. The training accuracy is 95% and the testing accuracy is 89%. We have shown the results in graphs in the figures below. The graphs are about the training and testing.

VGG16: Using the VGG16 model, we have obtained the train and test accuracy and loss graph along with the confusion matrix. From the graph, we can analyze the data loss and acquired concerning time. The graph of training and testing accuracy and loss of VGG16, along with confusion matrix:

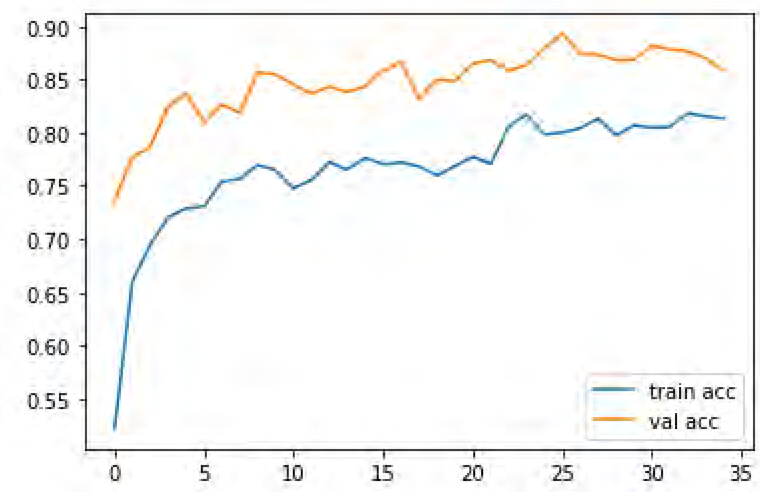

Figure 4.4: VGG16 Accuracy

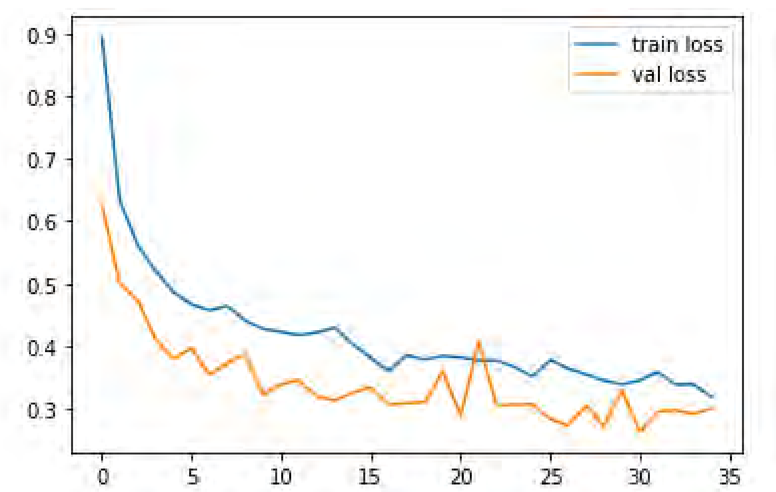

Figure 4.5: VGG16 Loss

	precision	recall	f1-score	support
normal	0.80	0.88	0.84	600
post	0.90	0.80	0.84	600
pre	0.89	0.90	0.90	600
accuracy			0.86	1800
macro avg	0.86	0.86	0.86	1800
weighted avg	0.86	0.86	0.86	1800

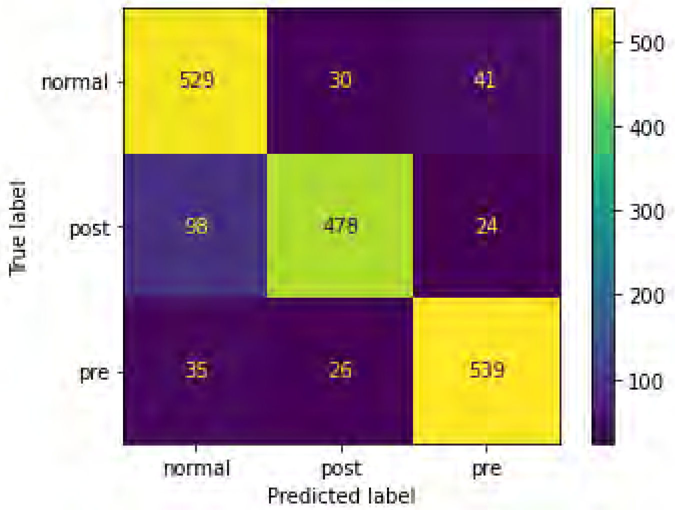

Figure 4.6: VGG16 Confusion Matrix

VGG19: Using the VGG19 model, we have done the same task, and we have seen that the accuracy acquired is 84%. The performance of the model is stated below with training and testing accuracy and loss of VGG19 along with confusion matrix:

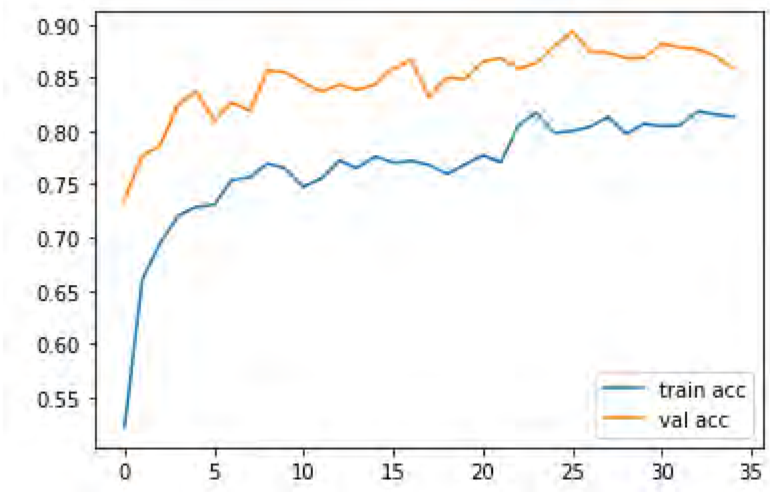

Figure 4.7: VGG19 Accuracy

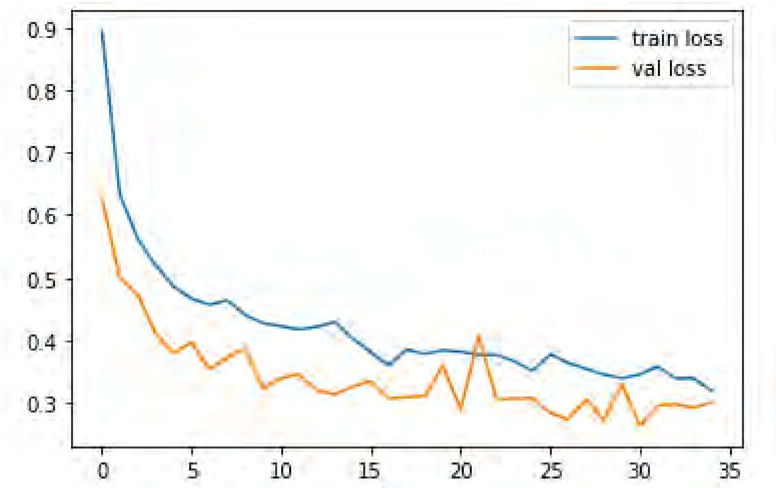

Figure 4.8: VGG19 Loss

	precision	recall	f1-score	support
normal	0.79	0.85	0.82	600
post	0.88	0.77	0.82	600
pre	0.85	0.90	0.87	600
accuracy			0.84	1800
macro avg	0.84	0.84	0.84	1800
weighted avg	0.84	0.84	0.84	1800

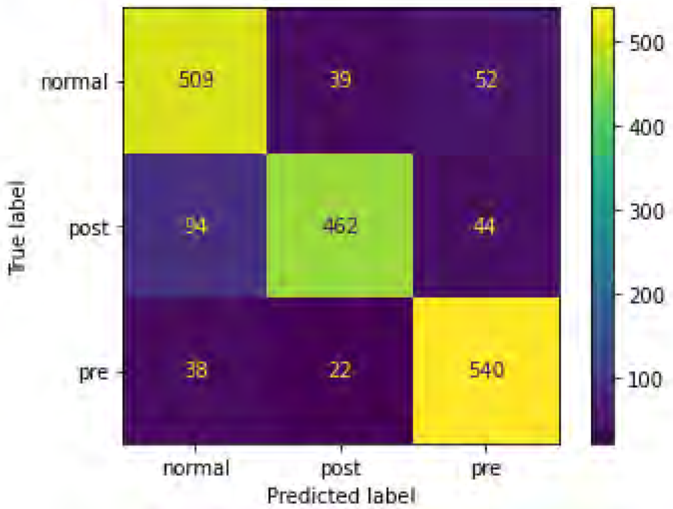

Figure 4.9: VGG19 Confusion Matrix

InceptionV3: In the InceptionV3 model, the accuracy we have acquired is 80%. Along with time, we can also learn about data loss. The performance of the model is stated below with training and testing accuracy and loss of inceptionV3, along with a confusion matrix:

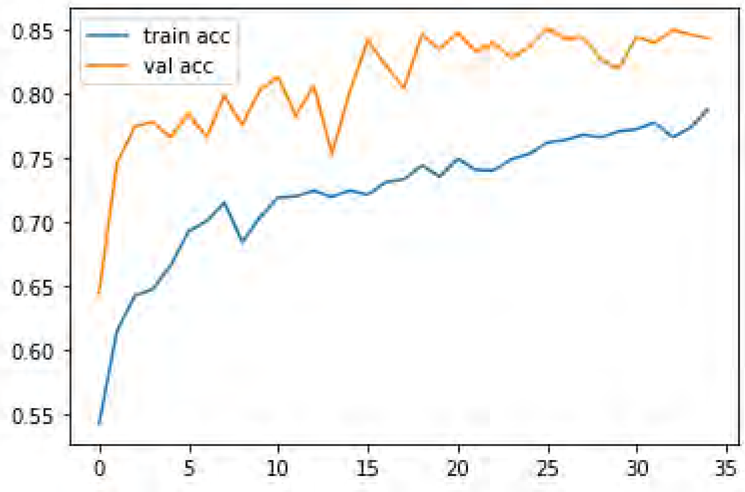

Figure 4.10: InceptionV3 Accuracy

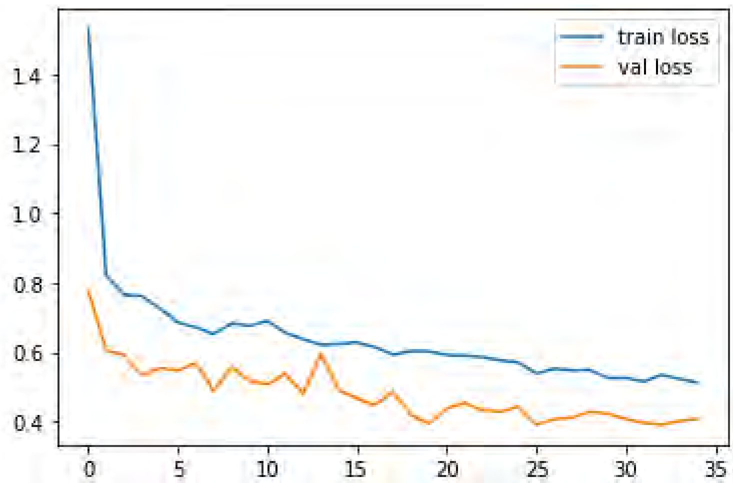

Figure 4.11: InceptionV3 Loss

	precision	recall	f1-score	support
normal	0.76	0.84	0.80	600
post	0.82	0.75	0.78	600
pre	0.81	0.80	0.80	600
accuracy			0.80	1800
macro avg	0.80	0.80	0.80	1800
weighted avg	0.80	0.80	0.80	1800

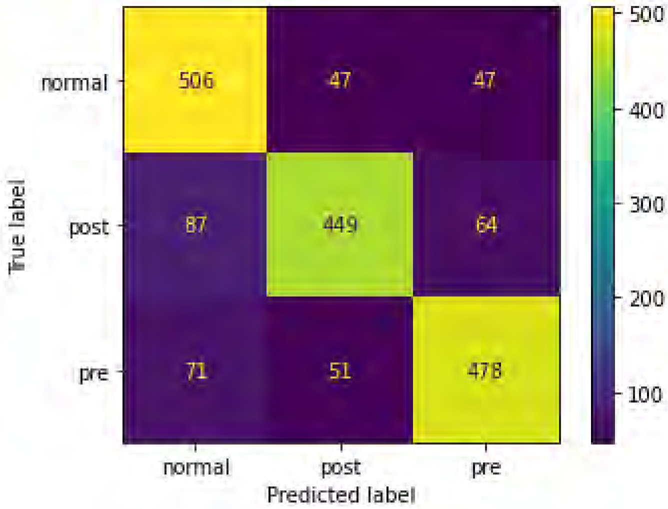

Figure 4.12: InceptionV3 Confusion Matrix

MobileNet: In MobileNet, the accuracy is 89%. The stated graph and matrix have shown the loss of data as well. The performance of the model is stated below with training and testing accuracy and loss of mobileNet along with a confusion matrix:

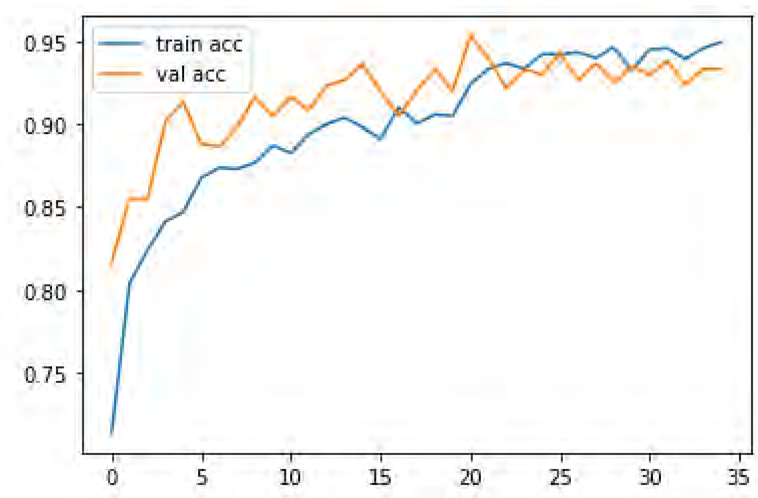

Figure 4.13: MobileNet Accuracy

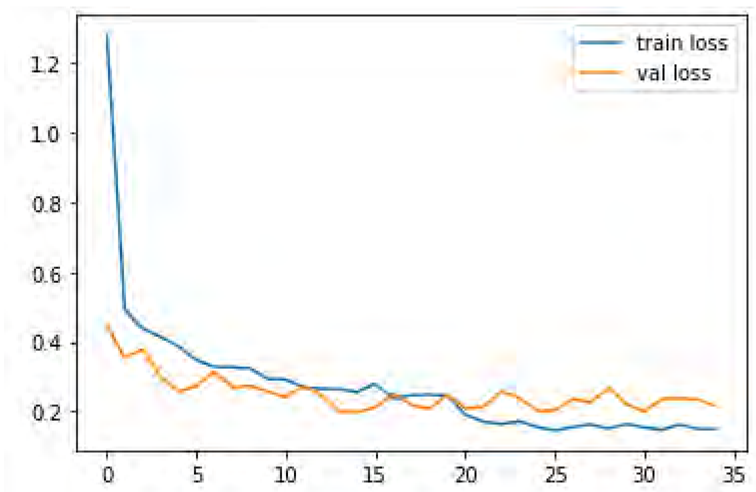

Figure 4.14: MobileNet Loss

	precision	recall	f1-score	support
normal	0.84	0.94	0.89	600
post	0.86	0.94	0.90	600
pre	0.99	0.78	0.87	600
accuracy			0.89	1800
macro avg	0.90	0.89	0.89	1800
weighted avg	0.90	0.89	0.89	1800

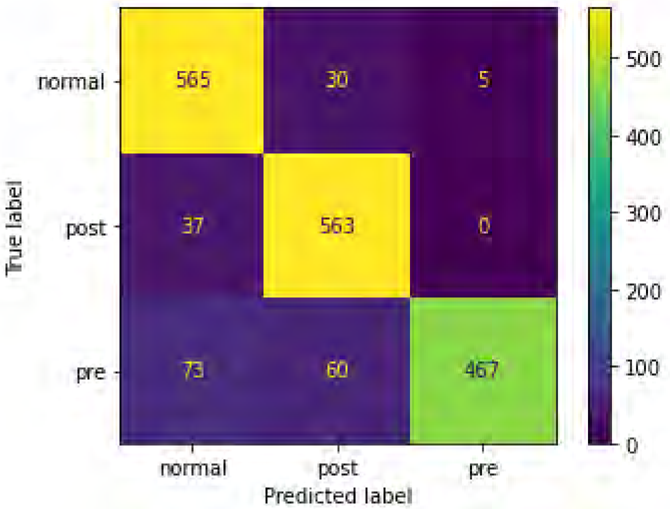

Figure 4.15: MobileNet Confusion Matrix

4.5 Performance of Ensemble Model

We have ensembled all the pre trained model and got this performance matrix table:

Table 4.2: Training and Test Metrics

Metric	Value	Metric	Value
Train Accuracy	93.8%	Test Accuracy	88.8%
Train Loss	20.5	Test Loss	33.6

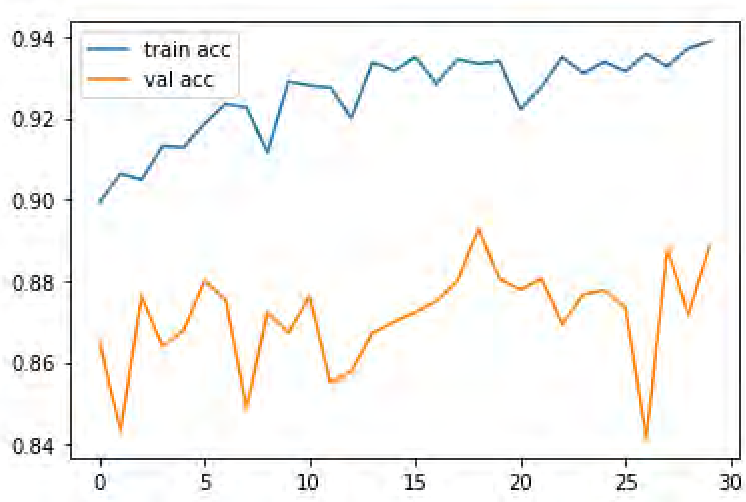

Figure 4.16: Ensemble Accuracy

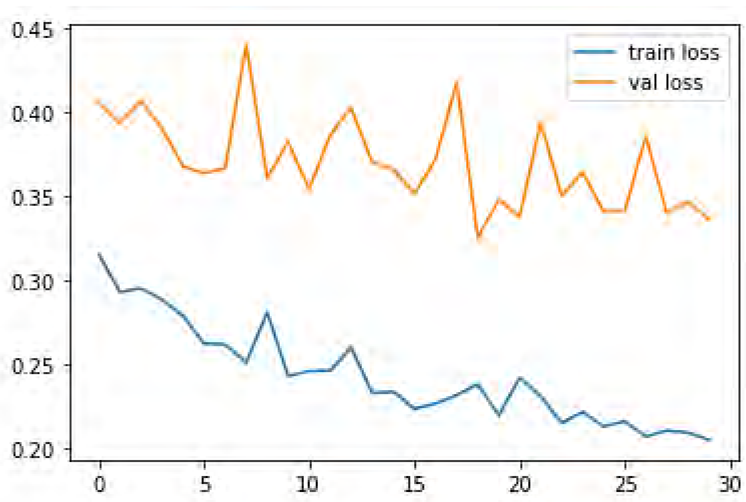

Figure 4.17: Ensemble Loss

4.6 Performance of Handcrafted Models

Here, we have used the HOG, MPV, and PO features on SVM and XGBoost.Upon several epochs, we have gained the scores that helped us determine the accuracy level of these models. The Performance matrices of SVM and XGBoost are given below:

Table 4.3: Performance Metrices Of SVM

Figures	**Hog**	**MPV**	**PO**
Test Accuracy	77.5%	70.4%	66.3%
Average Precision	77.3%	73.08%	63.2%
Average Sensitivity	84.5%	68.6%	71%
F1 Score	80.6%	70.7%	66.7%

Table 4.4: Performance Metrices Of XGBoost

Figures	**Hog**	**MPV**	**PO**
Test Accuracy	70.3%	63.8%	60.1%
Average Precision	69.7%	63.7%	57.03%
Average Sensitivity	74.5%	69.5%	70.5%
F1 Score	71.7%	66.4%	62.8%

4.7 Comparative Study

From the preliminary work we have done, the pre-trained model we have gained different levels of accuracy. Such as in VGG16 it is 86%, VGG19 84%, InceptionV3 80%, MobileNet 89%. From this analysis we have encountered, that these models cannot overcome our custom 13-layer CNN model which has given 91% accuracy. We sought another path to check whether our custom model is a better one for our data. We have used the ensemble method. All the pre-trained models have been ensembled, and later all of the ensembled models are merged into a single model we can see that the score is n 88%. We have also worked on our handcrafted feature extraction model where HOG, MPV, and PO are implemented on SVM and XGBoost. In SVM, the Hog feature showed 80%, MPV showed 70% and PO showed 66%. Likewise, we have also gathered the results of these 3 features in XGBoost which are 71% in HOG, 66% in MPV, and 62% in PO. All of these techniques still fail to outcome the accuracy we have gained from our custom CNN model which is 91%.

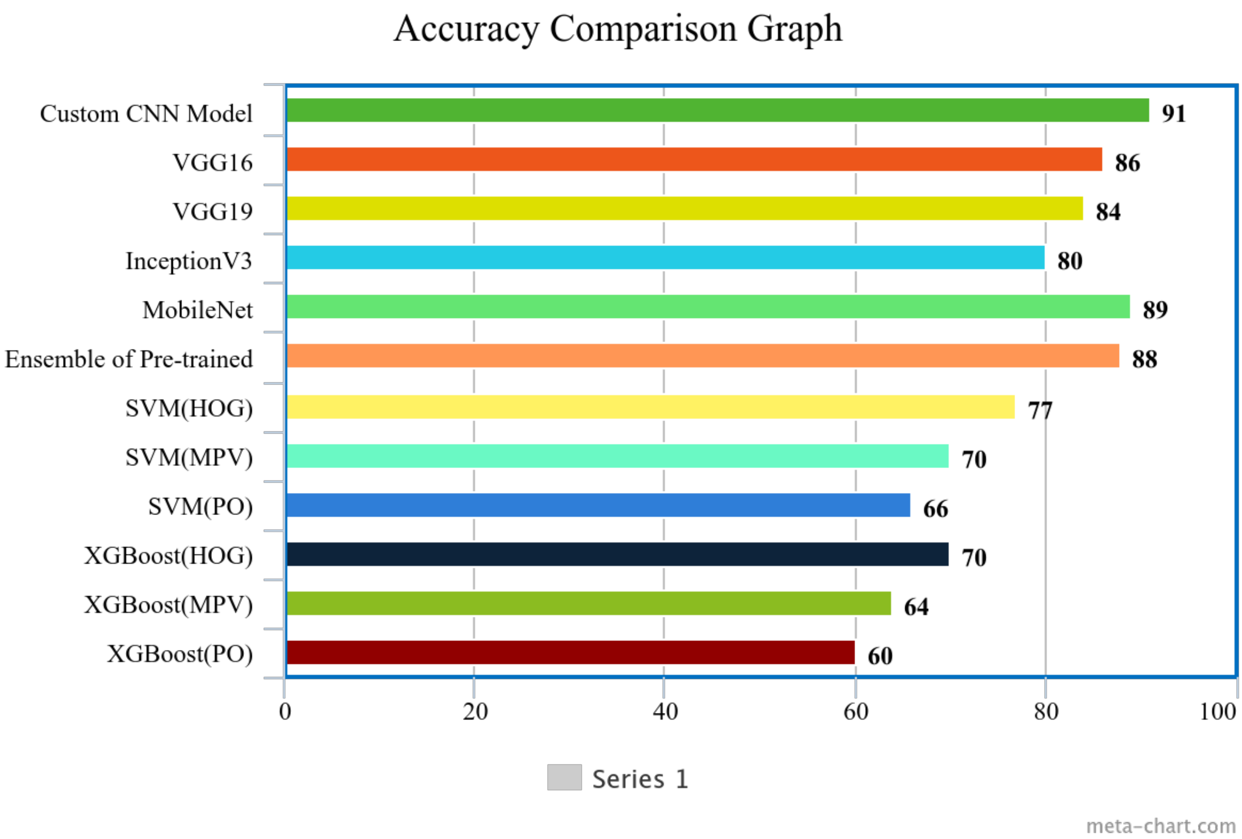

Figure 4.18: Accuracy comparison of implemented models

We may conclude, that though the proposed model is a lightweight one yet shows a better outcome for our dataset with a high accuracy rate compared to the other models we have worked on. Therefore, the use of transfer learning models on the same dataset shows us how effective the proposed model performs.

Chapter 5

Conclusion and Future work

5.1 Conclusion

The brain is like a supercomputer in our heads, controlling everything we do, think, and feel. It's a complex network of cells that helps us learn, remember, and experience the world around us. Detecting meningeal traumatic injury is vital as it safeguards the brain's protective coverings, preserves brain health, and prevents potential damage or complications. For the automatic classification and detection of traumatic meningeal injuries, a tailored deep-learning model has been proposed and created in this research paper. Pre-trained models are implemented and ensembled, for instance, VGG16, VGG19, MobileNet, and Inception V3, as the base architectures by using the capability of transfer learning. However, feature extraction of HOG, MPV, and PO was conducted, followed by their utilization in predictive modeling using XGBoost and SVM algorithms for comprehensive analysis and classification purposes. With a maximum accuracy of 91%, this research presents a deep CNN model that can detect efficiently. Our model offers a systematic, successful method for differentiating between traumatic meningeal damage detection on 7800 pictures, which are categorized into three groups. In terms of automatically identifying medical photos, the customized model's results show great potential. Timely diagnosis and treatment can improve patient outcomes; thus, it's important to accurately diagnose traumatic meningeal injuries. We also found that the suggested 13-layered CNN model is a superior way for traumatic meningeal image recognition when comparing it with earlier related research and transfer learning techniques. Compared to the other approaches, the customised model yields more accuracy. Despite this, we still want to improve and increase the model's efficiency.

5.2 Future Work

We have implemented our very first model and learned a lot, setting the stage to improve and explore more advanced techniques. We have achieved a satisfactory result, but there is still room for improvement in many areas. We would like to work on the following areas:

- We want to explore deeper CNN architectures or advanced neural network structures beyond the 13-layer model, which could further enhance accuracy in traumatic meningeal injury detection.
- We can investigate the potential of ensemble methods by combining multiple CNN architectures or incorporating other machine learning models to create a more robust and accurate predictive system for traumatic meningeal injury detection.
- We may conduct rigorous validation studies on diverse datasets, including real-world clinical data, to validate the model's performance in practical clinical settings. Evaluating the model's reliability, sensitivity, and specificity against various patient demographics and injury severity would be crucial.
- We want to explore the feasibility of deploying the model in real-time diagnostic tools or integrating it into existing medical imaging systems to assist clinicians in making faster and more accurate diagnoses.

These future research directions aim to further advance the accuracy, reliability, and applicability of the developed model for traumatic meningeal injury detection, ultimately enhancing its clinical utility and impact. It's important to keep in mind that deep learning is a subject that is always developing new approaches and structures. To use cutting-edge techniques for the automated classification and detection of traumatic meningeal injuries, we need to stay current on the most recent research and technological developments. The mix of creativity, subject-matter expertise, and a readiness to consider novel concepts will open the door for fascinating new research in this field.

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