BRAIN TUMOR ANALYSIS BY EXTRACTING FEATURES AND CLASSIFICATION THROUGH SUPPORT VECTOR MACHINES

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Abstract

Brain tumours are an increasing global epidemic, claiming millions of lives each year. Misdiagnosis can result in needless therapy and reduced life expectancy. Doctors have used computer-based diagnostic techniques such as DenseNet201 and the Gabor Filter to produce accurate diagnoses. In this work, SVM was used to classify independent features, and essential features were collected from an MRI image dataset using the DenseNet201 algorithm and Gabor filter. Deep convolutional layers outperform standard techniques in terms of extracting unique characteristics from target areas. An MRI dataset of 7023 brain tumour pictures from the Kaggle website was utilised to classify features using SVM. The hybrid approach of DenseNet201 and Gabor Filter produced the best overall results, with 98.02% precision, 98.01% accuracy, and 98.01% F1 score.

Index Terms: Support Vector Machines; Magnetic Resonance Imagiging (MRI) Data Set; Computer Aided Diagnosis Tools; Convolution Layers; Densenet201 Algorithm; Gabor Filter; Kaggle Website MRI Datasets.

INTRODUCTION

The brain, a complicated organ, is a major cause of cancer-related health problems and death rates worldwide. Brain tumors, affecting 4 to 5 people per 100,000 people annually, have a mortality rate of 2%. In Pakistan, with an estimated 150,000 new cases identified annually, brain tumors are a frequent issue. The high mortality rate of 60-80% indicates that a significant proportion of patients die from these tumors, highlighting the complexity of the brain's function. [1] Brain tumors are atypical clusters of cells that develop within or on top of the brain, damaging healthy cells and impairing brain function. These tumors are among the worst types due to their proximity to primary motor neurons. Early detection of brain cancer is crucial for successful treatment and survival. Advances in cancer treatment have improved early-stage identification, with early treatment initiators having a higher likelihood of survival than patients waiting until later stages. Small adjustments can have significant effects in the industry. [2]. Cells in the brain can form abnormal tumors, which can interfere with normal functioning. These cells pressure the brain, causing pain and other symptoms. The aggressiveness of a brain tumor determines whether it is benign or malignant. Malignant tumors are cancerous, while benign tumors are less damaging or dangerous to health. Therefore, understanding the difference between normal and abnormal brain cells is crucial for effective treatment.

Secondary cancers, which can originate in benign organs, can spread to other parts of the body via lymphatic or circulatory systems. Primary tumors do not spread, while secondary cancers, such as brain tumors, can begin in these organs and impair quality of life if untreated. [3]

Primary brain tumors, originating within the brain, can be classified as malignant or benign. Malignant tumors grow more quickly than benign tumors, and can penetrate nearby brain tissue, spread to other areas, and go undetected. Although benign tumors are not cancerous, they are located in the brain, a vital organ, making them dangerous. Malignant tumors rarely metastasize or spread to other parts of the body, making them a significant concern for healthcare professionals.
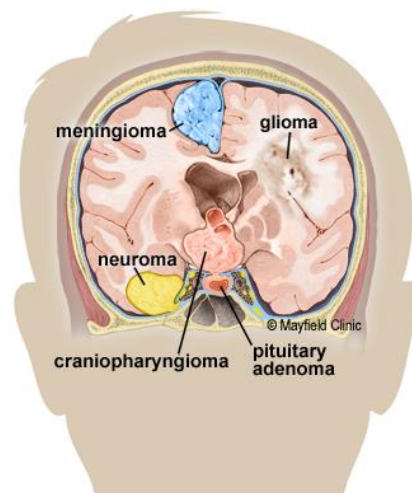

Figure 1: Brain Tumor Sites [4]

Metastatic tumors, which disperse from the primary tumor, can cause metastasis, the spread of cancer cells. Most primary tumors spread to the brain from the breast or lungs. These tumors can be fatal, regardless of their malignancy. The rigid skull of the brain can increase intracranial pressure, potentially crushing important structures. Certain tumors can also obstruct the flow of cerebrospinal fluid (CSF), causing ventricles to expand and resulting in hydrocephalus as mentioned in Figure 1. This can lead to edoema, or fluid buildup in the brain, due to the tumor's mass impact. Early identification of brain tumors significantly improves the patient's prognosis.

An early diagnosis can boost the chance of survival by up to 90%, according to study. The likelihood of a full recovery from brain tumors may be enhanced by early identification. However, because it takes time and money to hire qualified medical staff, early and precise diagnosis of brain tumors is rare. In this case, computerized brain tumour identification is useful. During the first stage of CAD, tumor detection can be automated with the use of specialized software. Magnetic resonance imaging (MRI), which provides precise images of the brain and can identify anomalies like tumors, is becoming more and more popular among medical professionals as a diagnostic tool. To

ascertain whether a tumour is present, the images are examined with the assistance of a physician and specialist software [5]. Much work has gone into creating automated techniques for identifying malignancies, particularly brain tumors, over the past few years. Medical image processing and sickness identification are two areas where artificial neural networks (ANNs) have made significant progress, particularly in tasks that were previously deemed to be challenging and required a real brain. Because of their effectiveness, the medical industry has come around to the usage of ANNs. Neural network artificial intelligence (AI) is expected to play a bigger role in the early detection of dangerous tumor masses as digital electronics and AI software develop. This paper explores the use of deep learning for feature extraction, machine learning for classification, and image processing for early brain cancer diagnosis. The processed and analyzed photos of brain tumors, four categories—meningioma, glioma, pituitary, and no tumor—have been identified.

RELATED WORK

The outcomes of various researchers' hard work in this literature on innovative approaches to brain tumour detection utilizing cutting-edge technology are promising.

Narmatha et al. [6] used brainstorming and fuzzy optimization to develop a novel approach for diagnosing brain tumours using magnetic resonance imaging (MRI). In contrast to fuzzy optimization, which uses numerous iterations to discover the ideal network topology, brainstorming optimization prioritizes and emphasizes cluster centers. Using the BraTS 2018 dataset, they evaluated their approach and got 94.77% and 93.85% accuracy, which is quite close. Togacar et al. [7] developed a BrainMRNet network employing module and hypercolumn methods.

Each raw picture was processed before being used in the attention module. The convolutional layer and important regions of the image were controlled by the attention module. The BrainMRNet model's convolutional layers made extensive use of the hypercolumn approach. Since we constructed the array tree of the final layer using data from each layer, we discovered that this technique had an accuracy of 96.05%. A unique method for segmenting and categorizing brain tumors with dynamic deep learning feature selection was introduced by Sharif et al. [8]. By boosting contrast and adding threshold to binary, a saliency map was produced. To increase the accuracy of the texture analysis, deep features were retrieved using the InceptionV3 pre-trained model and coupled with the dominant rotational LBP features.

The SoftMax function was then utilized to sort the combined vectors, and particle swarm optimization was employed to ascertain the optimal value. The study made use of datasets from BraTS 2017 and BraTS 2018. The BraTS 2017 dataset included an enhanced tumour score of 79.95%, a total tumour score of 93.7%, and a core tumour score of 83.73%. For the BraTS 2018 dataset, the corresponding values were 88.14%, 91.20%, and 81.84%. Amin et al. [9] developed a system that combines the four most essential magnetic resonance imaging (MRI) for brain cancer detection: T1C, T1, Flair,

and T2. We used discrete wavelet transformations and a Daubechies wavelet key. The residual artefacts were then removed using a partial differential diffusion filter. Damage zones were then segregated using a generic thresholding method. They tested the suggested strategy on five independent BraTS datasets and discovered that merging photos produced better results than individual sequences. Dandu et al. [10] developed a novel methodology for pancreatic and brain tumour (SIFT) identification that combines scaling transformations, statistical region merging (SRM), and cat swarm optimization (CSO) with a decision-based paired window median filter (DBCWMF).

Such approaches include BPNN classification and feature extraction using CSO and SIFT. The SRM approach was used to segment images and find defects, while the DBCWMF method was utilized to improve images.

The BPNN algorithm was used to categorise malignant tumours after lesion sites were extracted using the CSO and SIFT techniques. Using data from Harvard Medical School and the Cancer Imaging Archive, the researchers determined a 90.2% confidence interval. Kaur et al. [11] improved a large number of pre-trained deep convolutional neural networks (DCNNs) to handle new picture categories. Some of the DCNNs are AlexNet, GoogLeNet, ResNet101, ResNet50, InceptionV3, InceptionResNetV2, and VGG16. They evaluated these models using data from several sources, including the industry fact archive Figshare and Harvard Hospitals.

Approximately 40% was used for classroom instruction, with the remaining 60% used for assessment. The AlexNet model routinely beat competitors in testing and required the smallest amount of time to finish. Using data from the Figshare repository, the technique yielded results with 95.79% specificity, 90.65% sensitivity, and 91.51% accuracy.

A framework for deep feature extraction from brain MR images was created by Jaeyong Kang et al. [12] using a range of pre-trained deep convolutional neural networks and the concept of transfer learning. A set of machine learning classifiers was employed for analysis after they were extracted. We collected the top three deep features that did well on several machine learning classifiers to generate an ensemble of deep features that multiple classifiers could use to predict the final output. They compared the effectiveness of different pre-trained models as deep feature extractors, machine learning classifiers, and an ensemble of deep features for brain cancer classification using three publically accessible brain MRI datasets. The experimental results show that a set of deep traits can significantly improve performance.

Radial basis function (RBF) kernel support vector machine (SVM) generally outperforms other machine learning classifiers, especially when applied to large datasets. Every technique has an accuracy percentage ranging from 93% to 90%. Mohamed R. Shoaib et al. [13] used image processing and a convolutional neural network (CNN) to classify brain MRI scans as either a pituitary tumor, meningioma, or benign glioma. They tested their scratched CNN model against pre-trained inceptionV3, inceptionresnetV2, and CNN-based models using the transfer learning methodology.

To conduct the investigation, an MRI dataset of brain tumors was used. Patients with meningiomas accounted for 826 of the 826 MRIs, followed by glioma tumors (822), pituitary tumors (827), and healthy individuals (835).

Conversely, the accuracy of inceptionV3 was 85.34%, that of inceptionresnetV2 was 86.80%, and that of the CNN based on BRAIN-TUMOR-net was 91.24%. The transfer learning model demonstrated a low complexity rate and great effectiveness, with an accuracy rate of 93.15%. Somaya A. El-Feshawy et al. [14] proposed a convolutional neural network architecture model in this study to help categorize the various types of brain tumors. The performance of several current object detection techniques is also assessed. The recommended network architecture yielded noteworthy outcomes, with an overall accuracy of 96.05%. Using pre-trained ResNet50, InceptionV3, and Vgg-16 models, Onur SEVLİ [15] identified 253 brain MRI scans with and without malignancies in his study.

The edges of the brain tissue were identified by cropping and enlarging the raw image. Data augmentation was performed to balance out the class distributions in the dataset. Three different models were used to analyze the categorization process, accounting for characteristics including recall, accuracy, F1-score, and precision. With a 94.42% accuracy rate, an 83.86% recall rate, a 100% precision rate, and a 91.22% F1 score, the Vgg-16 model performed best. After that, the accuracy of the ResNet50 model was 82.49%. In line with previous studies, the InceptionV3 model did not fare well in this assessment. ResNet-18+SVM, ResNet-18, AlexNet+SVM, and AlexNet were all covered by E. M. Senan et al. [16] in their presentation of the hybrid deep learning models approach. Laplacian and average filters made the images look better. To extract deep and discriminating features, enhanced pictures were used to train deep learning models. We employed machine learning SVM algorithms and CNN classifiers SoftMax to identify deep features. Every suggested strategy for utilizing MRI scans to detect brain tumors was successful, and there was no variation in accuracy between the models. The computational cost of training the dataset varied greatly.

The AlexNet model needed 47 minutes and 35 seconds to train on the dataset. By comparison, 349 minutes and 13 seconds were needed to train the dataset using the ResNet-18 model. Recognizing a significant computational cost is necessary. On the other hand, hybrid approaches that combined CNN models with the SVM algorithm used very little computing power. The AlexNet+SVM hybrid model took 3 minutes and 21 seconds to train the dataset, compared to 2 minutes and 23 seconds for the ResNet-18+SVM hybrid model. A laptop equipped with a 6th generation Intel ® i5 processor, 12 GB of RAM, and a 4 GB GPU GEFORCE was used for the tests. The hybrid models of SVM and AlexNet outperformed all other models. It achieved 95.1% accuracy, 95.25% sensitivity, and 98.50% specificity. H. A. Munira et al. [17] revealed that a hybrid technique based on deep learning may efficiently detect different types of brain MR. The model was built in three steps: preprocessing, feature retrieval and classification with RF and SVM

classifiers, and feature extraction using CNN architecture. During the pre-processing stage, the photos were cropped, resized, and scaled.

To extract deep features from brain MRI, this study paired a novel CNN architecture with a pre-trained InceptionV3 model created using a transfer learning approach. The classifiers then carefully examined the particular properties discovered. This study thoroughly examined two brain MRI classification datasets using a combination of two deep CNNs and two distinct machine learning (ML) classifiers (RF, SVM). The pre-trained InceptionV3 model did not perform well in comparison to the specially constructed CNN model. The CNN model demonstrated a smooth border deception on test samples. Moreover, the CNN network might be more quickly and easily deployed than earlier pre-trained networks. Real-time performance of deep networks, like InceptionV3, requires specialized gear. All four models do not perform as well as the CNN-RF model (96.52%). Comparing the CNN-SVM model against the large Kaggle dataset—which include subclasses such as pituitary, glioma, normal, and meningioma—reveals a 95.41% performance difference.

Several image processing techniques were used by Osman Ozkaraca et al. [18] to identify the study's shortcomings. Using the dataset from their research, they conducted a series of trials prior to exploring the fundamental aspects of the CNN design. The investigation's findings indicate that the small number of levels in the classification causes a variety of problems. Next, we examined the construction of VGG16Net and DenseNet. They looked at these models to see how the usage of thick layers and the transfer learning approach affected the success rates. Research indicates that the health profession experiences very little influence from the transfer learning technique, even in cases where success rates are high in other disciplines.

DenseNet analysis was carried out after the transfer learning strategy was decided against in the study's model. Though not as much as expected, transfer learning does increase the success rate in thick layers. The decision was made to create a multi-tiered architecture and provide the training in person as a result. Throughout the preprocessing stage, the CNN architecture was used to maintain a high layer density in the finished model. As a result, the rate at which data is extracted has dramatically increased. It was decided that more data was required because the transfer learning technique was not going to be used. As a result, a dataset was found and made publicly accessible on Kaggle as a result of the investigation.

This dataset comprises the pituitary, meningioma, glioma, and no tumor categories. These categories contain about seven thousand photographs. Eighty percent of the dataset is used in the training phase, while twenty percent is used in the testing phase. T Large volumes of data used for training and the deep layer architecture of the suggested model were the main contributors to the predicted success rate. Throughout the training period, a success rate of 94-97% was attained because of the dense layers and lack of transfer learning procedures. Zaka Ullah et al.'s [19] main goal was creating a more precise system for classifying brain tumors. As its foundational models, this study

suggested employing CNN, VGG16, VGG19, InceptionV3, and ResNet101. The model began to perform better as data augmentation techniques were incorporated. For unseen photos, we achieved 95% F1-Measure, 97% Recall, and 95% Precision using three publically available datasets. Brain tumor presence and kind can be categorized using a method proposed by Geetha M et al. [20]. Without it, therapy, rehabilitation, and improved survival would be impossible. An experimental BT classification model built with the Sine-Cosine Archimedes Optimization Algorithm (SCAOA) yielded outstanding results. The input MRI brain picture was mostly obtained from databases and then sent to the preprocessing stage. The picture was then preprocessed with a Gaussian filter to eliminate extraneous noise.

For BT drives, we utilized SegNet that had been optimized using SCAOA. The suggested SCAOA is the result of merging AOA with SCA or the Archimedes optimization method. The next stage was to extract features from the segmented picture samples. When features for Bt detection were supplied, CNN was utilized to detect Bt based on the retrieved characteristics. If the detected output was determined to be a tumor, DenseNet was adjusted using the recommended SCAOA, and the BT image was categorized as gliomas, pituitary, or meningiomas tumors. With an accuracy rate of 93%, a specificity rate of 92%, and a sensitivity rate of 92.3 percent, SCAOA DenseNet ultimately produced impressive results as mentioned in table 1.

Table 1: To gain a better understanding of the previously mentioned research.

S. No	Studies	Utilized Dataset	Methodologies	Accuracy
1	Narmatha et al. [12]	BraTS 2018	Fuzzy and Brainstorm Optimization	93.85%
2	Togacar et al. [13]	Imaging Dataset	BrainMRNet network	96.05%
3	Sharif et al. [14]	BraTS 2017, BraTS 2018	The InceptionV3 plus SoftMax	83.73%, and 88.34% Respectively
4	Amin et al. [15]	Five BraTS datasets	CNN Model	87%
5	Dandu et al. [16]	HMS and CIA database	BPNN algorithm	90.2%
6	Kaur et al. [17]	BFR, Harvard, and clinics	Several pre-trained DCNNs	91.51%
7	Jaeyong Kang et al. [18]	MRI images Dataset	CNN pretrained models with SVM, and Fine Tuning	90-93%
8	Mohamed R. Shoaib et al. [19]	MRI Images Dataset	Transfer Learning, and DCNN with Pre-Trained Models	93%, and 91% Respectively
9	Somaya A. El-Feshawy et al. [20]	Imaging Dataset	CNN Architecture	96.05%
10	Onur SEVLİ [21]	253 Brain MRI Images	Several Pre-Trained Models	94.42%
11	E. M. Senan et al. [22]	MRI Images Dataset	Hybrid Model	95.1%
12	H. A. Munira et al. [23]	Kaggle MRI Images	DL Models with ML Classifiers	95.41%
13	Osman Ozkaraca et al. [24]	Kaggle MRI Dataset	CNN Models	94-97%
14	Zaka Ullah, et al. [25]	MRI Images Dataset	Several Pre-Trained DL Models	95%
15	Geetha M et al. [26]	MRI Dataset	SCAOA_DenseNet	93%

PROBLEM STATEMENT

One of the deadliest illnesses, brain tumors impact a large number of people. Although people with brain tumors often die from them, they can fully recover if they are detected and treated at an early stage. However, if the issue is not identified and treated in a timely manner, it may turn disastrous and unaffordable. This might result in death. Lowered training levels among radiologists raise the risk of misdiagnosis and human error. A surgical biopsy is used to take a tiny sample of tissue from the lesion location in order to do additional testing on the lesion. Conventional techniques for categorization and identification were potentially hazardous and intrusive.

X-ray, PET, CT, and MRI scans are among the medical image-based techniques that are now being utilized to find cancer cells. Each of these imaging modalities has certain characteristics that help in the classification of brain tumors. Magnetic resonance imaging (MRI) is currently the gold standard for classifying brain tumors, according to recent studies. When used on large patient populations, standard brain tumour detection appears laborious, intricate, and unfeasible. Due to a shortage of skilled radiologists and laboratory professionals, patient treatment may be exposed to human error.

As a result, the creation of an independent system is critical for appropriate interpretation of brain MR tumours. The proposed project will create a system based on machine learning and deep learning to swiftly and cheaply identify and categorize brain tumours using magnetic resonance imaging.

PROPOSED SYSTEM ARCHITECTURE

This research begins with an introduction of machine learning and deep learning, followed by the proposed technique and accompanying information Figure 2. This study employed three approaches to categorize MRI pictures associated to brain tumours: The first technique used DenseNet201 to extract the features of the MRI image dataset, which were subsequently categorized using the SVM algorithm. The same dataset was utilized in another approach that classified features using SVM and extracted features using the Gabor filter. Finally, we coupled the DenseNet201 and Gabor Filter functions and applied SVM for classification.

EXPERIMENTAL DESIGN

In this work, we evaluated the detection performance of brain tumours using the DenseNet201 model and the Gabor filter, both separately and in conjunction with the SVM classifier. The schematic below (Figure 4.1) shows the brain tumor detection technology employed in this experiment.

The important task of brain tumour identification was initially carried out using the 201-layer DenseNet201 design with a dense link network. DenseNet201 extracts color, shape, and texture from medical images using convolutional layers and filters to deliver the complex pattern recognition needed for precise diagnosis. While the bottleneck layers

effectively compress and decompress feature maps, guaranteeing parameter efficiency, the architecture's distinctive dense connectivity promotes feature reuse and information flow across levels. 94080 features were taken out of each MRI image to create a feature map of 7023 x 94080.

The features were further classified as meningioma, glioma, pituitary, or no cancer using the support vector machine classifier. The characteristics were extracted using the Gabor filter, image analysis, and SVM classification into four categories: Meningioma, Glioma, Pituitary, and No-Tumor. Finally, the features formed by concatenating the features acquired by applying the Gabor and DenseNet201 filters were classified using Support Vector Machines (SVM). As so, it developed into a hybrid approach.
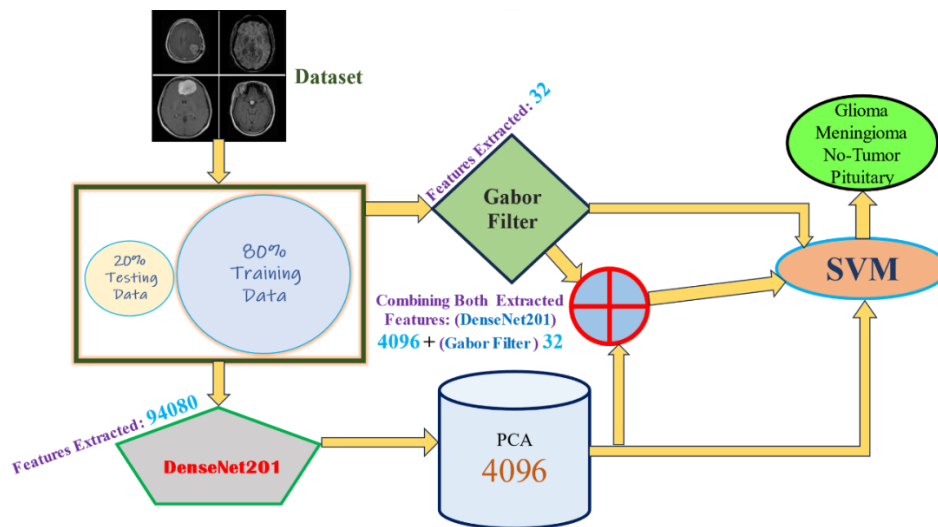
Figure 2: Experimental Design

METHODOLOGY

Deep Learning

Deep learning techniques, notably deep neural network methods, have been employed recently to assist medical professionals, enhance the precision of medical imaging diagnosis, and identify diseases early on. Traditional CNNs have trouble understanding medical images due to their size, color, and intricate structure. Curriculum learning is one solution for this, whereby the system is gradually exposed to progressively complicated concepts. However, in order to employ deep learning algorithms properly and prevent overfitting, a substantial amount of data is usually needed. Obtaining such a vast dataset may present challenges when working with significant medical diseases. CNNs can get over this restriction by artificially expanding the dataset through the use of augmentation techniques. The three main parts of a convolutional neural network (CNN) are fully connected, pooling, and convolutional layers. Convolutional layers use convolution kernels to convolve an input array in order to extract characteristics such as forms, colors,

lines, and edges. Feature maps, also known as pooling layers, are used to minimize a feature map's dimensionality by gathering features on a local and global scale, then transferring the highest or average value of those characteristics. Finally, fully linked layers of a Convolutional Neural Network (CNN) make decisions that regulate operations like regression and classification. The loss during training is calculated as the difference between the actual and predicted values [21]. The CNN architecture's numerous layers allow the training data to incorporate millions of features and thousands of pictures, resulting in promising and accurate classification accuracy. To address this issue, convolutional neural networks (CNN) employ information augmentation techniques such as rotation, translation, scaling, and translation. The CNN type DenseNet201 [22] is employed in this study.

Machine Learning

Machine learning, a fast emerging science, has the potential to profoundly revolutionize how we approach problem solving in the future. The purpose of this branch of artificial intelligence is to create computer algorithms capable of detecting patterns in data, learning from them, and making judgements or predictions without human involvement. Machine learning models are trained on datasets to improve their prediction accuracy. Finally, machine learning systems should be able to utilize their training data to properly anticipate new experimental data. The model's parameters are changed using the training and validation data sets for generalization. The model's generalizability can be objectively measured by its performance on the test set. There are many different types of machine learning algorithms, such as supervised, unsupervised, and reinforcement learning methods. The promise of these methods is being recognized by a number of fields, including predictive modeling, natural language processing, and picture recognition. Support vector machines (SVMs), feed-forward neural networks (BPNNs), kernel neural networks (KNNs), and artificial neural networks (ANNs) are a few machine learning techniques [29, 30, 31]. Medical practitioners utilize machine learning algorithms to accurately categorize biological imaging images including MRI photographs of brain tumors. Machine learning is a dynamic field that is always changing and improving with new discoveries. This makes it a fascinating and difficult subject for additional research.

Dataset Description

This work's dataset was created by combining three datasets from the well-known Kaggle website [23]: figshare, Br35H, and SARTAJ. These datasets were combined to create a bigger dataset that included 7023 MRI images of the human brain. Following that, the data set was divided into two groups: 80% for training and 20% for testing. Four classes are produced based on the photos in the training dataset: Glioma (1321 images), Meningioma (1339 images), No-Tumor (1595 images), and Pituitary (747 images). In a similar vein, the testing dataset consists of images of 306 Meningiomas, 300 Gliomas, 405 No-Tumor images, and 300 Pituitary images. For the No-Tumor class, the pictures were taken from the Br35H dataset. For a more comprehensive analysis of the models'

performance, this dataset provides a large and diverse collection of photos to train and evaluate. Figure 3 shows some representative images from the MRI dataset.
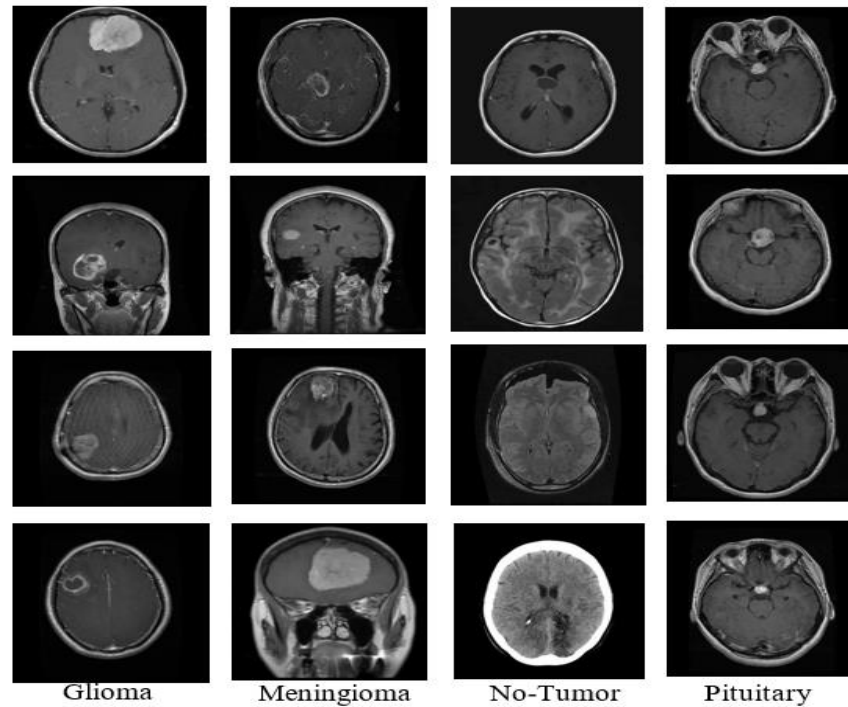

Figure 3: Kaggle's MRI dataset

RESULTS

This study classified and evaluated MRI images of brain tumors using a variety of methods. The data used in this study included 512 training photographs and 1311 testing photos from the meningioma, glioma, no-tumor, and pituitary classes.

Experiment 1 Result

The first method extracted visual features using a convolutional neural network called DenseNet201. PCA was then used to reduce the dimensionality of the features for every image in the dataset to 4096. These attributes were then categorized using the SVM classifier. With this approach, the F1 score, accuracy, and precision were all 97.10%. A confusion matrix and ROC curve were also created using this method.

CM of Experiment 1

The confusion matrix in the first approach (DenseNet201+SVM) could be used to evaluate how accurately the classifier labels data. The confusion matrix displayed the actual class names in the rows and the anticipated class labels in the columns, as you may recall from before. The classifier identified most of the 284 glioma photographs accurately. 285 images from the Meningioma class were correctly predicted by the classifier, with very

few images being incorrectly classified into other groups. When the class No-Tumor is applied, very few or no photos are reclassified into other classes, and a large proportion of 404 images are correctly predicted. Pituitary performed remarkably well, earning a perfect score on 300 photographs. Figure 4 demonstrates how well the first method's confusion matrix (DenseNet201+SVM) identified most of the images.
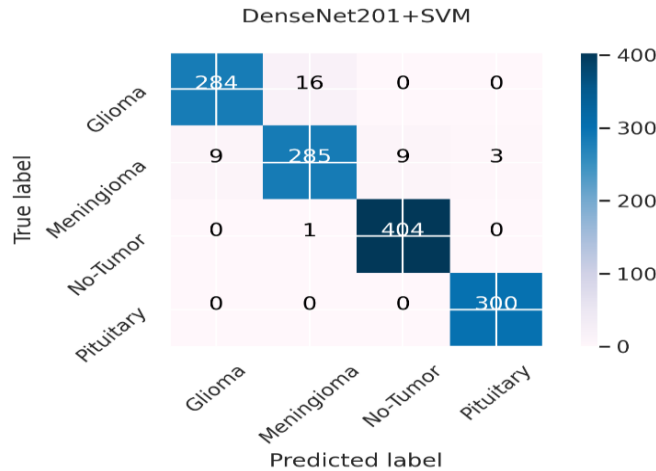

Figure 4: SVM CM using DenseNet201

ROC Curve of 1st Experiment

The CM in Figure 4.1 shows that true positives, or diagonals, indicate right predictions, whereas off-diagonals, or false positives, indicate incorrect predictions. The classifier's overall performance as well as the classes in which it is succeeding or failing can be ascertained using the matrix. The study's area under the curve (AUC) for pituitary, meningioma, and no tumor was 100%, 99% for glioma, and 100% for no tumor, as Figure 5 illustrates.
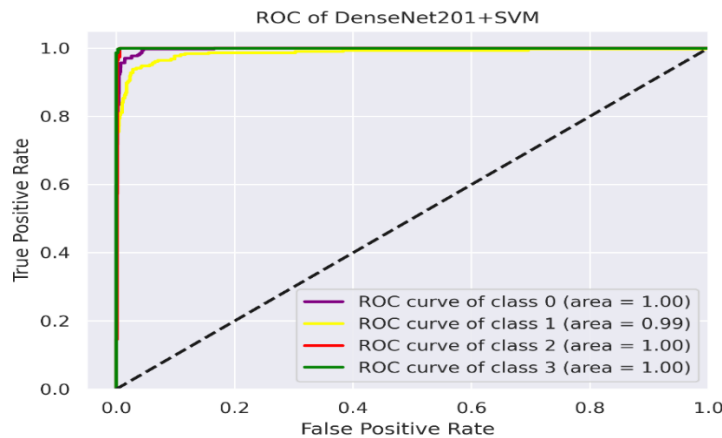

Figure 5: SVM ROC using DenseNet201

Results of 2nd Experiment

In the second method, after feature extraction using the Gabor filter, the MRI images were classified using a support vector machine (SVM) for machine learning. With a precision of 58.25%, an F1 score of 56.27%, and an accuracy of 62.93%, this approach produced positive results. An in-depth analysis of the outcomes led to the creation of a confusion matrix. This study produced a ROC curve as evidence of the classifier's effectiveness.

8.1.2.1 CM of Experiment 2

In the matrix cell at the first row and column intersection, 229 images in the Glioma class have been correctly classified as gliomas, as shown in Figure 6. Similarly, the value 10 in the cell at the intersection of the first row and second column represents the number of images of the class Glioma that the model incorrectly classified as Meningiomas. The result matrix shows that while the algorithm performed well in the meningioma and pituitary categories, it struggled in the glioma and no tumor categories.
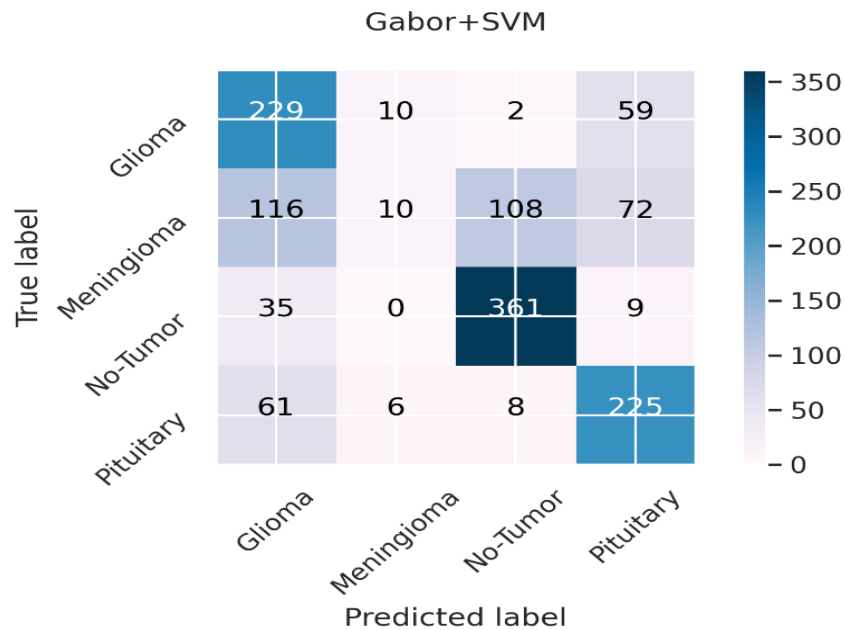

Figure 6: Gabor+SVM's CM

ROC Curve of 2nd Experiment

This experiment's ROC curve (Gabor+SVM) shows how the threshold value and the FPR and TPR are related. A classifier's area under the receiver operating characteristic (ROC) curve can be used to assess its overall performance. The performance of the classifier can be evaluated by calculating and contrasting the AUC values for each class. The study's area under the curve (AUC) values were 90% for pituitary, 87% for meningioma, 76% for no tumor, and 94% overall, as shown in Figure 7.
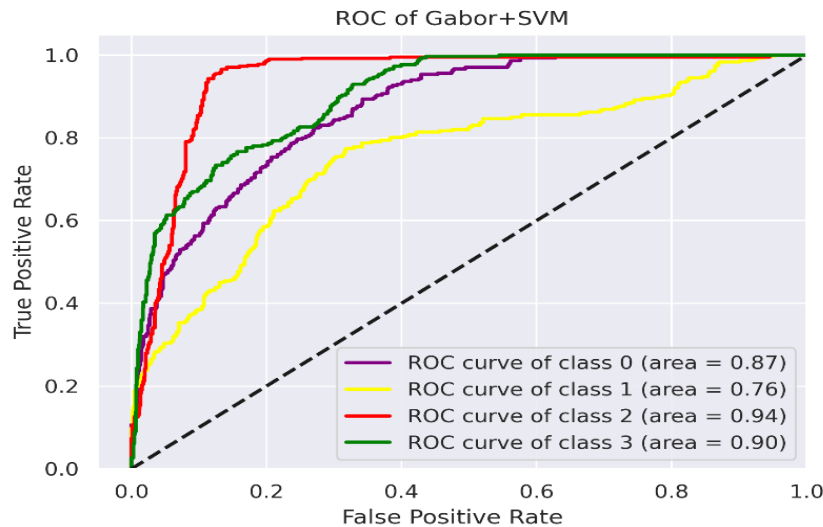
Figure 7: ROC Curve for Gabor+SVM

Results of Experiment 3

Principal component analysis (PCA) is used in both techniques to reduce the feature space; 4096 features are extracted from the pictures using DenseNet201 in the first method, while 32 features are extracted using the Gabor filter in the second. Following their combination in the third step, all 4128 characteristics were classified using the SVM classifier. With 98.02% precision, 98.01% F1 score, and 98.01% accuracy, this approach yielded the best outcomes. Confusion matrix and ROC curve construction were further steps in this process.

CM of Experiment 3

The third technique's confusion matrix (DenseNet201+Gabor+SVM) showed the classifier's performance on the test data, among other things. The intended class labels are displayed in the matrix's columns, while the actual class names are displayed in the rows. Each row of the matrix displays the percentage of samples that the classifier properly or incorrectly classified. Gliomas, no tumor, meningiomas, and pituitary tumors are the four types of tumors that each row and column in the matrix represents. You can see the total number of correctly identified photographs by class along the diagonals of the matrix. The off-diagonal components showed how many photos were wrongly labeled. Using the combined approach confusion matrix, accurate identifications of 290 glioma, 299 pituitary, 405 no tumour, and 291 meningioma images were obtained. Six of the sixty images that were analyzed were misidentified as gliomas, seven as no tumors, two as pituitary tumors, ten as meningiomas in the glioma class, and one as a meningioma in the pituitary class, as shown in Figure 8.
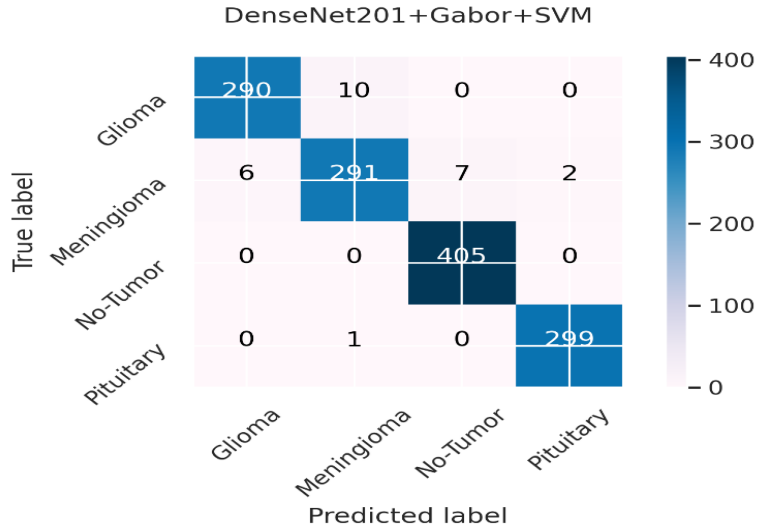
Figure 8: CM of SVM for DenseNet201 Combined Features with Gabor Filter

The confusion matrix demonstrates how the classifier for this approach performed better than the ones for its predecessors in terms of the number of correctly categorized photographs, accuracy, precision, and f1 score.

ROC Curve of Experiment 3

The study found that the area under the curve (AUC) values for pituitary, meningioma, glioma, and no tumor were 100%, 99%, 100%, and 100%, respectively in Figure 9.
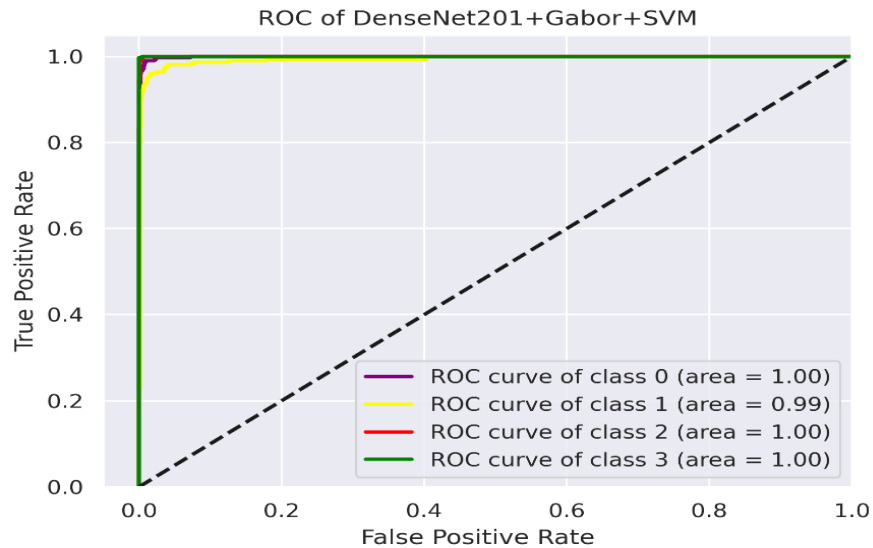

Figure 9: ROC Curve of SVM for Combined DenseNet201 and Gabor Filter Features
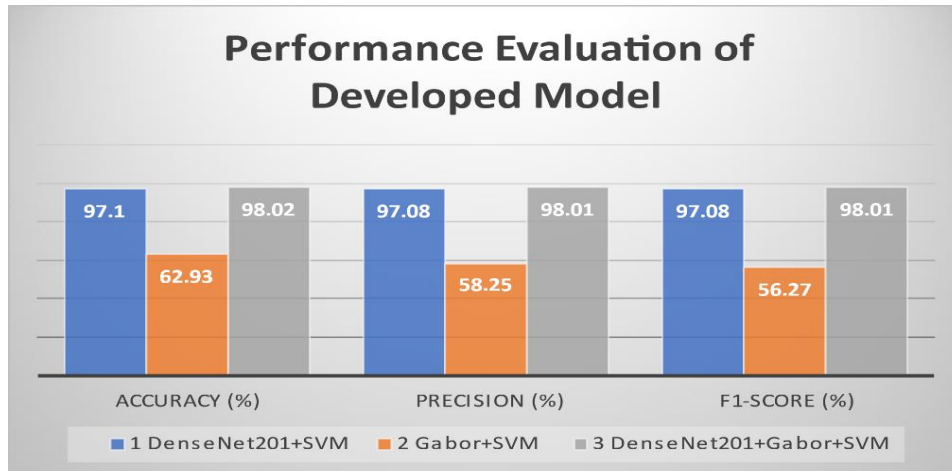
Performance Evaluation of Developed Model

Figure 10: Assessing the Developed Model's Performance

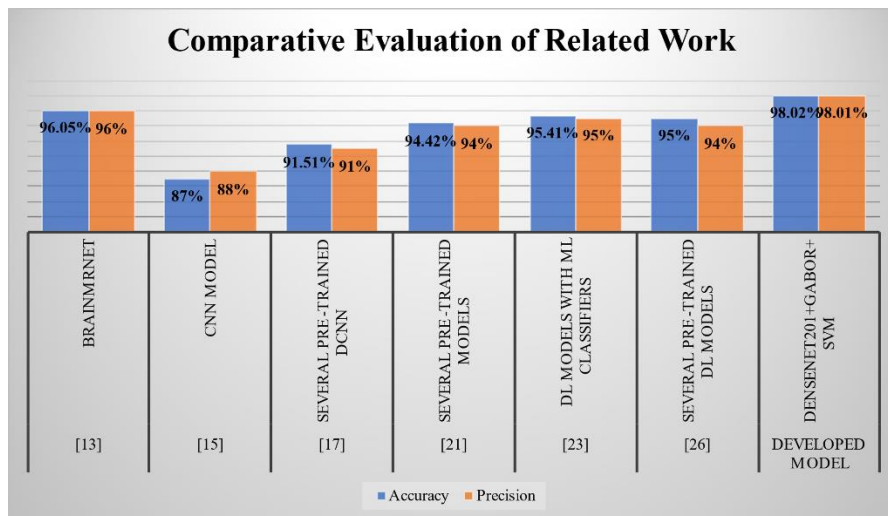**Comparative Evaluation of Related Work**

Figure 11: Evaluating This Work in Light of the Past

CONCLUSION

This thesis presents a system that combines machine learning, deep learning, and handcrafted methods to accurately diagnose brain tumors in the Kaggle MRI imaging dataset. First, we used the MRI image set to extract features using the DenseNet201 architecture. Following PCA dimensionality reduction, feature classification was performed using the SVM approach. Gabor filters were used to extract features, which were subsequently categorized using Support Vector Machines (SVM). The latter technique classified the data using features derived via a Gabor filter and DenseNet201,

followed by an SVM classifier. The suggested method's performance was assessed using a variety of measures, including area under the curve (AUC), F1 score, precision, and accuracy.

The combination of Gabor Filter and DenseNet201 produced the greatest results, with a f1 score reading of 98.01%, accuracy of 98.02%, and precision of 98.01%. The suggested approach categorized a brain tumour MRI image accurately, as seen below.

FUTURE WORK

To improve the suggested approach, deep learning architectures may be combined with other image processing algorithms. Its adaptable architecture allows you to work with a wide range of data. This step also allows for the optimization and improvement of characteristic extraction and classification algorithms. Improves the model's generalizability by testing it on a wider and more varied dataset. In the future, the feature extraction approach might be refined to produce cutting-edge deep learning models such as InceptionV3 and others. Combining the approach with other medical imaging modalities, such as CT or PET pictures, improves its diagnostic effectiveness. More research is needed in the critical areas of using real-time technology and enhancing the efficacy of practical applications.

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