Pakistan Journal of Engineering and Technology, PakJET
ISSN (p): 2664-2042, ISSN (e): 2664-2050
Volume: 6, Number: 1, Pages: 42- 50, Year: 2023

An Intelligent Hybrid Approach for Brain Tumor Detection

Sajeed Ullah[1,3], Mehran Ahmad[1], Shahzad Anwar[2,3], and Muhammad Irfan Khattak[1]

[1]Department of Electrical Engineering, University of Engineering and Technology (UET), Peshawar, Pakistan
[2]Department of Mechatronics Engineering, University of Engineering and Technology (UET), Peshawar, Pakistan
[3]Artificial Intelligence in Healthcare (AIH), IIPL, NCAI, University of Engineering and Technology (UET), Peshawar, Pakistan

Corresponding author: Sajeed Ullah (e-mail: sajeedullah-msece@uetpeshawar.edu.pk).

Received: 05/10/2022, Revised: 20/01/2023, Accepted: 10/02/2023

***Abstract-* Brain tumours are quickly increasing in prevalence all over the world. It causes the deaths of thousands of individuals annually. Misdiagnosis of brain tumours often results in unnecessary treatment, further lowering the survival rate of the affected individuals. Prompt medical diagnosis is crucial to improve the prognosis for patients with brain tumours. Positive advancements in deep and machine learning domains have been made due to repeated achievements in supporting medical practitioners in making correct diagnoses utilizing computer-aided diagnostic tools. Deep convolutional layers are superior to conventional methods at extracting unique characteristics from target regions. In this research, initially, Gabor filter and ResNet50 were applied to accurately extract the important features of brain tumours from the MRI images dataset. Firstly, the extracted features of Gabor and ResNet50 were classified individually through SVM, and secondly, the features from both these techniques were combined and then classified through SVM. The Kaggle MRI dataset for a brain tumour was utilized in this research. It includes 7,023 Images and four classes Glioma, Meningioma, No-Tumor, and Pituitary. The results from every system were outstanding, but the best results were shown by the combined features of Gabor and ResNet50, an advanced hybrid approach with 95.73% accuracy, 95.90% precision, and 95.72% f1 score.**

***Index Terms--* Gabor, MRI Images, PCA, ResNet50, SVM.**

I. INTRODUCTION

The human brain is a complex and vital organ formed by a collection of billions of nerve cells, which are responsible for various operations. The excessive growth of abnormal cells in the human brain leads to brain tumours. A brain tumour deteriorates the number of healthy brain cells, so it could disturb the usual functions of the brain. Some are benign (non-cancerous) in the brain, and some show malignancy (Cancerous). When the brain cells grow abnormally and form tumours, called a primary tumour. When other cancerous body parts affect the brain and form a tumour, it is called a secondary tumour or metastatic. There are several types of brain tumours considering their location, texture, shape, and size. The most common are meningioma, pituitary, and glioma [1]. World Health Organization classifies diseases as benign or malignant and defines four classes of brain tumours Grade (I-IV) [2].

Grade I and Grade II are thought of as lower-grade tumours, while the malignant brain tumours of Grade III and Grade IV grow too fast, and after reaching the other parts, it affects the healthy cells there as well. By classifying the brain tumours utilizing MRI images or other than MRI images, radiologists or clinicians could predict the type early, how far the tumours have affected the brain and could be able to suggest the proper cure [3], [4]. According to the worldwide cancer data website World Cancer Research Fund International (WCRFI), the estimated total number of cancer cases was 18.1 million in 2020, including 9.3 million men and women and 8.8 million cases. This record shows that cancer-related to the Brain (Central Nervous System) was on 19th number of total new recorded cases of brain cancer, 308,102 (Men 168,346 and Women 139,756), which was about 1.7% of overall cancers [5]. The Pakistan Global Cancer Observatory disclosed a fact sheet regarding cancer in 2020. The Brain (Central Nervous System) rank was 11th in newly registered cases and 9th in death-registered cases in overall cancers. Total new brain cancer cases were 4770, and deaths were 3934 [6].

A tumour biopsy is a surgical procedure in which a tissue sample is taken from the tumour region for further examination. After studying and examining the sample, a decision is taken about which type of tumour is this, and treatments are accordingly suggested. This conventional technique of detecting the tumours was invasive and complex. To overcome this complexity and invasiveness, several tools were invented, which could classify the brain's images accurately for the tumours. These non-invasive methods exploit images for visualization of brain tumours, i.e., Magnetic Resonance Imaging (MRI) images, Computer Tomography (CT) scans, Single-Photon Emission Computerized Tomography (SPECT), X-Rays and Positron Emission Tomography (PET). MRI images are considered a standard of care for practice in clinics [7]. The images produced by Magnetic Resonance Imaging (MRI) are clear and explicit as compared to Computerized Tomography (CT) scans. For example, if a doctor wants to view soft tissues like brain tumours, a better choice is MRI Images as compared to CT scans or X-rays [8].

Distinguishing tissues that are normal in the brain from those that are abnormal is a critical step in detecting brain tumour type. Because of location, size, and shape varieties, the detection of brain tumours turns out to be stimulating and yet an open issue. The idea of processing medical images is utilized in analyzing brain tumours (i.e., segmentation, detection, and classification). As a brain tumour is a chronic, fatal disease that could cause death, early detection is necessary. The manual examination of the MRI images by practitioners, radiologists, and clinicians could lead to human error, be prone to misdiagnose, and be time-consuming.

Moreover, early tumour detection is very unlikely [9]. A brain tumour is a lethal disease, so detecting brain tumour type at an early stage is necessary, and it could play an important role in the treatment and saving of a patient's life [10]. Thus, overcoming all the limitations formerly discussed in the manual technique of detecting brain tumour types at a very early stage, a computerized-based automated system was developed for classifying, segmenting, and detecting brain tumours. This automatic system is composed of several crucial steps: MRI image pre-processing, extraction of aimed features, and finally, classification based on an algorithm of supervised learning [11]. The essential step in this process is classification, performed either by machine learning or deep learning.

A computer system is trained to do jobs which is why called an expert system, like the classification of images on machine learning. It is utilized in the medical field, whether it is for treatment or teaching purposes. Pre-processing is an important step in medical image classification for feature extraction; For instance, imaging data from various sources is utilized to identify and classify brain tumours. Robust ML algorithms are exploited to classify brain tumour-related images (datasets) containing ANN, BPNN, SVM, K-NN, and PNN [12]. Deep learning (DL) is an emerging technology gaining popularity and widespread interest in all fields, especially in medical imaging analysis [13]. Deep learning improves flexibility and capability by analyzing irregular input over numerous layers. Feature extraction might occur at each successive layer and be sent along [14]. The prominent feature of deep learning is attaining the needy data from a dataset automatically. It is mostly applied to images related to the medical area. It automatically extracts prominent features and classifies images accordingly [15].

The proposed methodology is a hybrid because it exploits the machine with deep learning to acquire the highest accuracy.

II. LITERATURE REVIEW

This section provides a comprehensive summary of previous techniques utilized for brain tumour detection and classification. Numerous researchers who devoted their efforts to achieving promising results by employing advanced techniques for diagnosing brain tumours are mentioned in this literature.

By combining the methods of fuzzy and brain-storm optimization, Narmatha et al. [16] created a novel technique for classifying brain tumour MRI images. While fuzzy optimization was carried out through repeated iterations to determine the best network structure, brain-storming optimization was emphasized and prioritized the cluster centers. They tested their suggested method utilizing the BraTS 2018 dataset and achieved high results with 93.85% accuracy, 95.77% sensitivity, 95.42% F1 score, and 94.77% precision. Togacar et al. [17] employed the modulo and hypercolumn technique to create a network called BrainMRNet. Raw images were processed before the attention module was applied. The convolutional layer and the significant sections of the image were under the control of the attention module. The hypercolumn technique was widely employed in the BrainMRNet model's convolutional layers. Since the data from each layer was employed to populate the final layer's array tree, the accuracy of this approach was calculated to be 96.05%. Sharif et al. [18] introduced a new method for segmenting and classifying brain tumours by utilizing active deep learning-based feature selection. A saliency map was produced by contrast enhancement and threshold into binary. In addition, the InceptionV3 pre-trained model was utilized for deep features retrieval, which was then joined with the (LBP features) dominant rotated to produce a more accurate texture analysis. Next, this research utilized the SoftMax function to sort the combined vectors, utilizing particle swarm optimization to get their best value (PSO). The research utilized BraTS 2017 and BraTS 2018 datasets. Dice scores for the core, total and enhanced tumours on the BraTS 2017 dataset were 83.73 %, 93.7 %, and 79.95 %, respectively. For the BraTS 2018 dataset, the corresponding values were 88.34 %, 91.2 %, and 81.8 %. T1C, T1, Flair, and T2 are four of the most important MRI image sequences for detecting brain cancer, and Amin et al. [19] devised a strategy for combining their textural and structural characteristics. For this purpose, this research utilized a Daubechies wavelet kernel and discrete wavelet transforms. After that, a partial differential diffusion filter was applied to eliminate any remaining artifacts. Then, a global thresholding method was employed to partition the lesion areas. On five different BraTS datasets, they discovered that the findings achieved by merging the images were superior to those obtained by utilizing individual sequences, lending credence to the efficacy of the proposed approach. The method has an 87% accuracy rate, 92% sensitivity, and 80% specificity.

Utilizing CNN's ability to differentiate between malignant and benign tumours, M. O. Khairandish et al. [20] presented a hybrid strategy for classifying brain tumours MRI images on a publicly available dataset called BraTS 2015. Due to their superior performance, deep learning techniques have become increasingly popular in recent years for image classification. With its various techniques, CNN could extract features and achieve higher classification accuracy without the need for manually created models. The proposed hybrid model combines threshold-based segmentation for detection, CNN, and SVM for classification. Numerous accuracy results from prior studies have been obtained, including 95% for DCNN, 94.233% for RELM, 96% for DWA and DNN, 97.5% for CNN, and 96.6% for KNN. The overall accuracy for the suggested CNN-SVM hybrid model was 98.4959 %. To find brain tumours in MRI data, Gini Grag and Ritu Grag [21] suggested a Majority Voting Method-based hybrid ensemble approach that employs Decision

Tree (DT), K-Nearest Neighbor (KNN), and Decision Tree (DT). KNN-RF-DT, a hybrid ensemble classifier based on the Majority Voting algorithm, was employed for classification. SWT, PCA, and GLCM were employed for feature extraction, and Otsu's threshold approach was utilized for segmentation. The approach utilized traditional classifiers to boost performance; these classifiers benefit from small dataset requirements and low processing time complexity, making them suitable for usage by people with less expertise. The method obtained an accuracy of 97.305% when tested on a dataset of 2556 images, with 85% utilized for training and 15% utilized for testing. To identify and classify various forms of brain tumours utilizing MRI images, Isselmou Abd El Kader et al. [22] developed a differential deep-CNN. Classifying brain tumours with MRI was challenging for several reasons, including the brain's complexity, the overlap of tissues, the brain's high density, and so on. The proposed model takes advantage of differential deep-CNN differential operators in the architecture to extract extra differential feature maps from the initial maps of CNN features, thus enhancing the performance of the proposed technique. The introduced model had a 99.25% accuracy rate when evaluated and trained on a dataset of 25,000 MRI brain images, both pathological and normal.

With the help of the U-NET CNN and fuzzy logic architecture, Maqsood et al. [23] were able to detect brain tumours. U-NET CNN classification, edge detection utilizing fuzzy logic, and contrast enhancement were all utilized in this procedure. Before a dual tree-complex wavelet transform (DTCWT) was employed on several scales at the images of different sources, they were contrast-enhanced. To find the edges in the improved images, a fuzzy logic-based edge detection (FLBED) method was exploited. Decomposed sub-band images of the brain were classified utilizing the classification algorithm U-NET CNN, yielding features that can be utilized to distinguish Meningioma brain tumours, among others. This method's accuracy was 98.59% compared to several newly created algorithms. Raza et al. [24] proposed a hybrid deep-learning model for gliomas, meningiomas, and pituitary tumours.

The GoogLeNet served as the foundation for a simple CNN architecture that was utilized to generate the model. To make the model more expressive, this research omitted the final five GooLeNet layers and added 15 more. This feature map also made use of leaky ReLU activation. The suggested model outperformed all other utilized approaches, obtaining 99.67% accuracy, 99.6% precision, 99.66% F1 score, and 100% recall. The need for early, accurate medical diagnosis of brain cancer was emphasized by M. Senan et al. [25], as was the track record of success of computer-aided diagnostic tools in assisting clinicians in making such diagnoses, especially in the region of the machine and deep learning. Utilizing ResNet-18, AlexNet, and SVM, several projects classify and diagnose brain tumours utilizing a deep and machine learning hybrid approach. After MRI images were improved with an average filter, deep learning algorithms were employed to extract reliable and deep essential features by utilizing deep convolutional layers. The 3,060 images in the MRI dataset reflect three distinct types of cancer and one type of normal tissue. Achieving 95.10% accuracy, 98.50% specificity, and 95.25% sensitivity, the AlexNet+SVM hybrid method outperformed the other methods. Brain tumours were a leading cause of death, as noted by M. Rasool et al. [26], who also underlined the significance of detecting them early for treatment. Even though a biopsy was necessary for the conventional classification of brain tumours, it was not always taken care of before surgery. With machine learning and other technological breakthroughs, radiologists may now use MRI images to diagnose malignancies without resorting to invasive treatments. MRI images of three distinct brain cancers were proposed to be classified using a CNN-based architecture, a novel hybrid approach.

The proposed method combines a GoogleNet model of the CNN algorithm with a classifier, either a support vector machine (SVM) or a soft-max, to categorize patterns and extract features. Brain MRI scans revealed 1426 gliomas, 708 meningiomas, 930 pituitary tumours, and 396 scans of healthy brain tissue were used to test the approach. An SVM classifier with GoogleNet as a feature extractor yielded a 98.1% accuracy rate. For radiologists, an accurate technique for recognizing and classifying brain tumours was proposed by Sarmad Maqsood et al. [27]. First, they utilized linear contrast stretching to improve the sharpness of the source image's edges; second, utilization of a 17-layer deep neural network architecture specifically for brain tumours segmentation; third, they modified a version of the MobileNetV2 architecture for feature extraction and training via transfer learning; and finally, an entropy-based controlled method to choose the best features. And last, the classification of brain tumours utilizing a multiclass support vector machine (M-SVM). The suggested technique achieved 97.47% and 98.92% accuracy in tests using datasets from BraTS 2018 and Figshare, respectively. In this case, eXplainable Artificial Intelligence (XAI) was used, and the outcomes demonstrated that the suggested approach outperformed existing methods and could improve the field of medical imaging.

III. MATERIALS AND METHODS

This study evaluated the Gabor filter, ResNet50 model, and SVM classifier for brain tumour detection. The diagram below shows the study's brain tumour detection technique (Fig. 1).

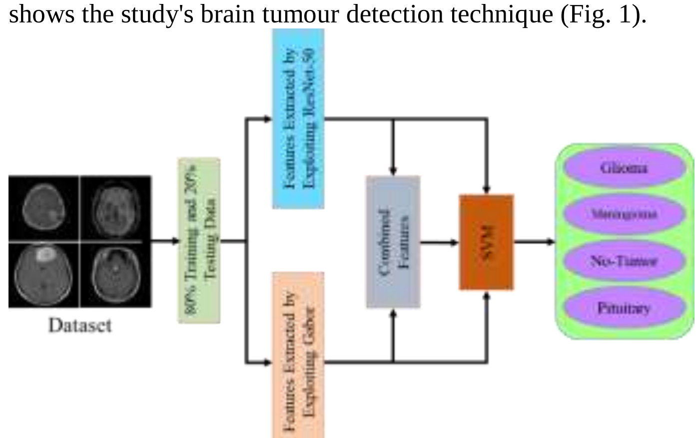

FIGURE 1. Proposed Methodology

From the images, important features were extracted by utilizing the Gabor filter, and SVM classified these as Glioma, Meningioma, No-Tumours, and Pituitary. Second, ResNet50 architecture found brain tumours in MRI images. ResNet50 has fully linked, pooling, convolutional layers. The convolutional layers pass each input image through filters (3x3 and 5x5) that extract regionally different features and store them in activation maps. These maps transferred the best features to the next layer. Layers of Pooling decreased the image size and design expense to speed up the process. Resnet50 convolutional layers extracted brain tumours' texture, shape, and colour. Extracting 100352 features from each MRI image yielded a 7023 x 100352 feature map. Glioma, Meningioma, No-Tumours, and Pituitary were then classified utilizing SVM machine learning. Finally, SVM classified the combined Gabor filter and ResNet50 features, it became a hybrid.

A. DATASET DESCRIPTION AND SPLITTING

Three different datasets—figshare, SARTAJ dataset, and Br35H—from the popular website Kaggle [28] were combined to create the dataset utilized in this research. To create more generalized algorithms, these datasets were combined to produce a larger dataset of 7023 MRI images of the human brain, split into the Training data about 80%, and Testing data about 20% of the overall dataset. The training data was further divided into four classes: Glioma (contains 1321 images), Meningioma (contains 1339 images), No-Tumours (contains 1595 images), and pituitary (contains 1457 images). Similarly, for the case of a testing dataset, which contains four classes: (Glioma contains 300 images), meningioma (contains 306 images), No-Tumours (contains 405 images), and pituitary (contains 300 images).

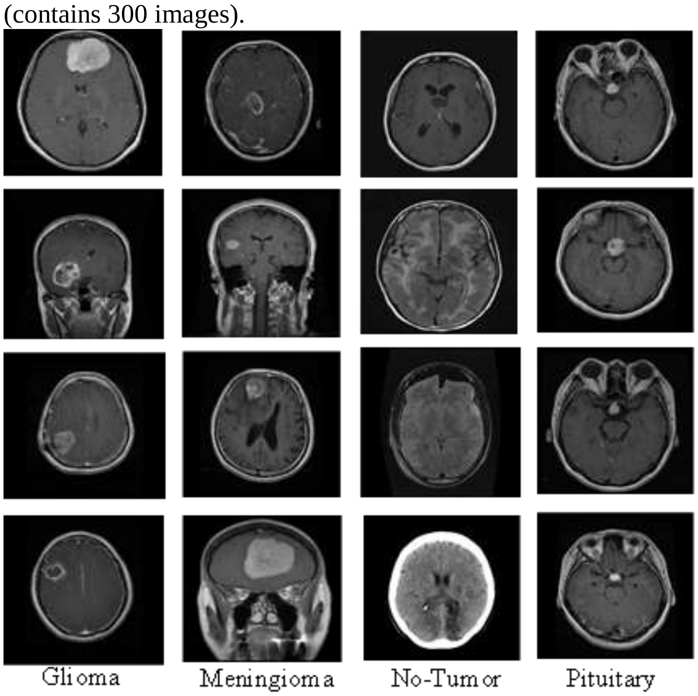

FIGURE 2. Sample Images of MRI dataset

The images in the No-Tumours class were sourced from the Br35H dataset. This dataset provides a large and diverse set of images for the training and evaluation of the models utilized in this study, allowing for a more robust analysis of the performance of the models. (Fig. 2) shows a few samples of images from the mentioned dataset.

B. SVM CLASSIFIER UTILIZATION FOR GABOR FEATURES

As illustrated in the first approach, Gabor filter features were retrieved and classified by SVM (Fig. 3).

FIGURE 3. Gabor+SVM

The sinusoidal wave and Gaussian function were tuned for different frequency and orientation properties. Pre-processing enhanced image quality and classifier performance. The filter, as defined by Gabor in [29], is given by:

$$G(x, y, \lambda, \theta, \sigma, \psi) = e\hat{}\left(-(x'^2 + \gamma^2 * y'^2)/2\sigma^2\right) * \cos(2\pi * x'/\lambda + \psi) \tag{1}$$

where x, and y are image pixel coordinates, λ is the wavelength of the sinusoidal wave, θ is the orientation of the filter, σ is the standard deviation of the Gaussian function, and ψ is the phase offset of the sine wave, $x' = x * \cos(\theta) + y * \sin(\theta)$, $y' = -x * \sin(\theta) + y * \cos(\theta)$ and γ is the aspect ratio of the Gaussian function (usually set to 1 for isotropic filters). Medical imaging often uses the Gabor filter [30], [31]. The Gabor filter extracted 32 features for each image. An SVM classifier classified brain MRI images utilizing Gabor filter features. The SVM algorithm was a common supervised learning method utilized in image classification [32]. SVM classifiers discover the maximum-margin hyperplane that separates classes in high-dimensional feature spaces. Kernel functions let SVM handle high-dimensional data and non-linearly separable scenarios. The retrieved features from the brain MRI dataset taught the classifier.

C. SVM CLASSIFIER UTILIZATION FOR RESNET50 FEATURES

As illustrated in the second approach, ResNet50 extracts features, and SVM classifies them (Fig. 4). ResNet50 is a multi-section DCNN. The initial convolutional layer, residual blocks, and subsequent convolutional and fully connected layers provide the network's output. The network's performance depends on each section's function. ResNet50 learns residual functions from layer inputs utilizing residual connections instead of the original mapping. Allowing the network to learn residual functions instead of the original mapping reduces vanishing gradients. Because ResNet50 could now train networks deeper than previously anticipated, it could extract more exact information from images. This approach extracted 100352 ResNet50 features for each image in the 7023-image dataset.

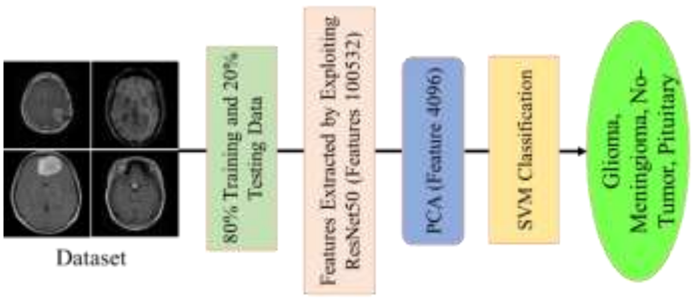

FIGURE 4. ResNet50+SVM

PCA reduced feature dimensionality. PCA, a linear dimensionality reduction technique, could discover data patterns and project them onto a lower-dimensional space with as much information as possible. PCA finds the principal components, or directions of maximum variance, then projects the data onto a new coordinate system with these directions as the axes. PCA was utilized to reduce ResNet50's 100352 features to 4096. The data were projected onto a new coordinate system with the directions of maximum variation as the axes. The data's dimensionality was decreased while maintaining most of its information. PCA reduced data dimensionality and improved classifier calculation, allowing SVM to classify images. PCA reduced the dimensionality of the features, and the SVM classifier identified images. It classified images as Meningioma, Glioma, No-Tumours, or Pituitary for this investigation.

D. SVM CLASSIFIER UTILIZATION FOR COMBINED FEATURES

The third and final technique indicated that the Gabor filter and ResNet50 features were integrated and classified utilizing SVM (Fig. 5).

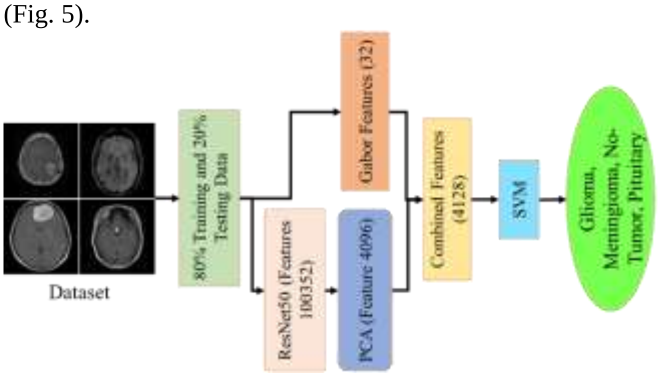

FIGURE 5. Gabor+ReseNet50+SVM

Gabor filter and ResNet50 features from MRI images enhanced the performance of the utilized classifier. Gabor linear filters found edges and textures in images. This research extracted 32 Gabor filter features from each image of the dataset images. These features were combined with 4096 ResNet50 features acquired through the principal component analysis to yield 4128 features. Combining features trained and tested an SVM classifier. After training on 5712 images, the classifier was tested on the test dataset (1311 images). Gabor filter and ResNet50 features in combined form improved classifier performance.

IV. RESULTS AND DISCUSSION

This section delves into the approaches employed in this research, including the features extraction techniques, classification technique utilized, evaluation measures applied, and performance analysis conducted. The results obtained were thoroughly discussed and compared with those found in previous studies and were illustrated through the use of relevant figures and tables. Three approaches were employed in this research for the extraction of features from the MRI images of brain tumours, and then the classification of these features through SVM. The dataset utilized for this research consisted of 4 classes: Meningioma, Glioma, No-Tumours, and Pituitary, with a total of 5712 training images and 1311 testing images.

A. RESULT OF SVM CLASSIFIER UTILIZED FOR GABOR FEATURES

In the first approach, images were Gabor-filtered and classified employing an SVM classifier. This yields 56.27% F1 scores, 62.93% accuracy, and 58.25% precision. A confusion matrix and ROC curves were also created to evaluate the results and demonstrate the classifier's effectiveness. The confusion matrix showed the model's classification accuracy for each class. Each confusion matrix cell showed the number of images the model classified as a specific class.

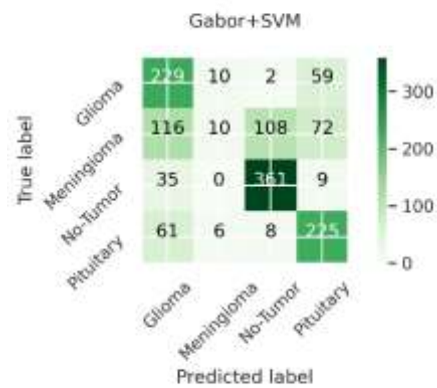

FIGURE 6. Confusion Matrix of Gabor+SVM

The confusion matrix (Fig. 6) shows that the model correctly classified 229 Glioma images. The model misclassified 10 Glioma images as meningioma in the cell at the first row and second column intersection and so on. From the matrix, the model scored well for Glioma and No-Tumours but struggled to classify Meningioma and Pituitary images. Gabor+SVM's ROC curve shows how threshold values affect TPR and FPR. ROC curves were used to quantify how well a classifier performs. It calculated and compared class AUC values to evaluate the classifier's performance. The confusion matrix divided true positives into diagonals and false positives into the off-diagonals. The confusion matrix evaluated the classifier's overall performance and identified its strongest and weakest classes. As indicated in (Fig. 7), Glioma AUC was 87%, Meningioma 76%, No-Tumours 94%, and Pituitary 90% in this research.

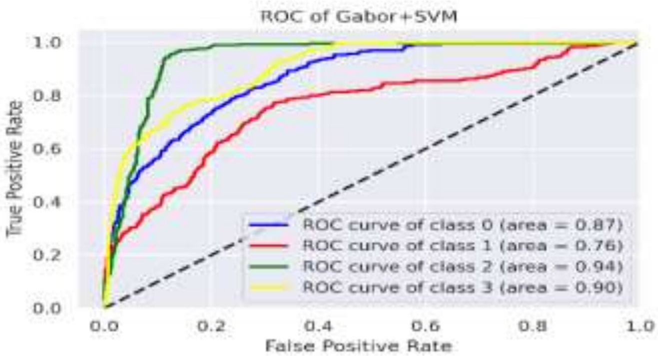

FIGURE 7. ROC Curve of Gabor+SVM

B. RESULT OF SVM CLASSIFIER UTILIZED FOR RESNET50 FEATURES

In the second approach, the ResNet50 convolutional neural network retrieved features from images, then Principal Component Analysis (PCA) reduced feature dimensionality to 4096 for each dataset, then SVM classifiers classified these features. This approach yielded a 95.26% F1 score, 95.27% accuracy, and 95.35% precision. The algorithm was evaluated through a confusion matrix and ROC curve. The confusion matrix for the approach (ResNet50+SVM) includes evaluating the classifier's labelling accuracy. With few false positives in the training set, the classifier correctly identified most 266 Glioma images. The classifier predicted several Meningioma images with low misclassification to other classes. Best was No-Tumours, which classified 403 images correctly, and low misclassification to other classes.

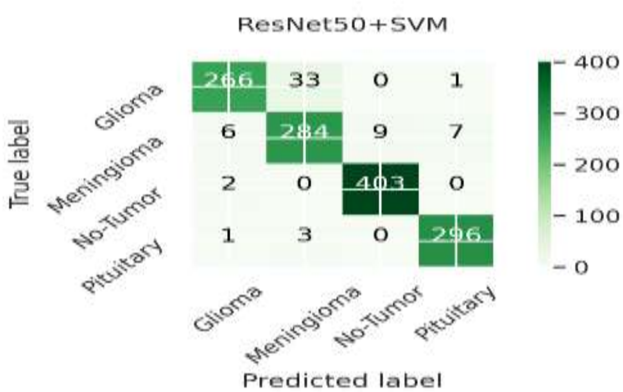

FIGURE 8. Confusion Matrix of ResNet50+SVM

This confusion matrix showed that the second approach (ResNet50+SVM) correctly identified most Meningioma, No-Tumours, and Pituitary images but struggled with Glioma images (Fig. 8). In the confusion matrix (Fig. 8), diagonals represent true positives (correct predictions), and off-diagonals represent false positives (incorrect predictions). The matrix could evaluate the classifier's overall performance and identify its strongest and weakest classes. This research showed that Glioma, Meningioma, No-Tumours, and Pituitary AUC values were 100%, 99%, 100%, and 100%, respectively (Fig. 9).

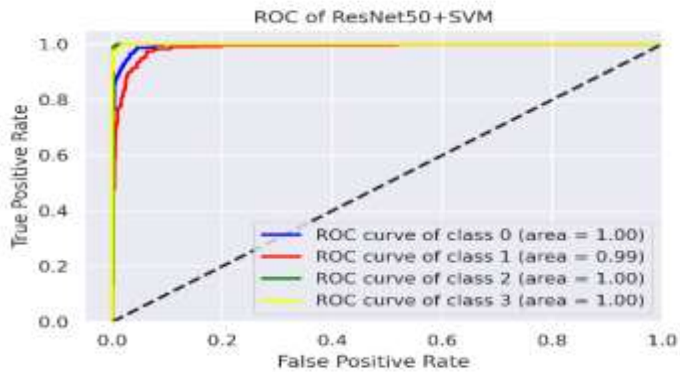

FIGURE 9. ROC Curve of ResNet50+SVM

C. RESULT OF SVM CLASSIFIER UTILIZED FOR COMBINED FEATURES

The third method combined the 4128 retrieved features from the images utilizing the Gabor filter 32, ResNet50 convolutional neural network, and PCA to lessen the dimension of the features to 4096. The SVM classifier was then employed, classifying these combined features with an accuracy of 95.73%, a precision of 95.9%, and an F1 score of 95.72%. For this approach, a confusion matrix and ROC curve were also produced. Among the others, the confusion matrix for the third strategy (ResNet50+Gabor+SVM) demonstrated the classifier's best performance on the test data. Each entry in the matrix displayed the fraction of samples that were properly or incorrectly identified by the classifier. Glioma, Meningioma, No-Tumours, and Pituitary—were represented by the four rows and columns of the matrix. The diagonal elements of the matrix represented the number of images that were successfully classified for each class. The off-diagonal elements showed the number of improperly classified images.

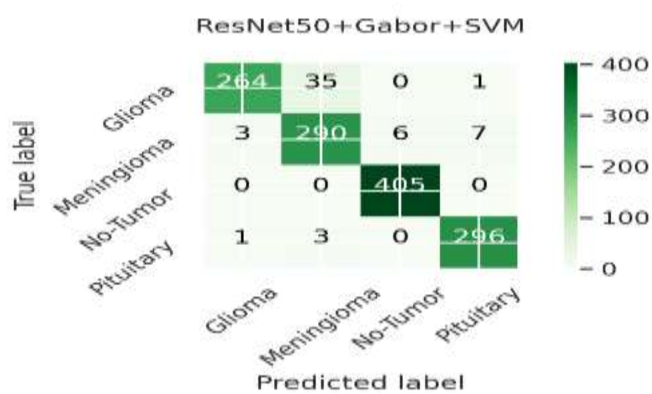

FIGURE 10. Confusion Matrix of Gabor+ResNet50+SVM

In the confusion matrix of the combined approach, the classifier correctly classified 264 images as glioma, 290 images as meningioma, 405 images as No-Tumours, and 296 images as pituitary. However, it incorrectly classified 35 images as meningioma, 0 images as No-Tumours and 1 image as Pituitary for Glioma class, 3 images as glioma, 6 images as No-Tumours and 7 images as Pituitary for Meningioma class, 0 images as glioma, 0 images as meningioma and 0 images as Pituitary for No-Tumours class, similarly 1 image as glioma, 3 images as meningioma, and 0 images as No-Tumours for Pituitary class as shown in the (Fig. 10). This confusion matrix demonstrated that the classifier achieved the best performance relative to the other approaches concerning the accuracy, precision, and f1 score, and a large number of correctly classified images. In the confusion matrix (Figure 10), the diagonals represent true positives, where correct predictions were made, while the off-diagonals represent false positives, where incorrect predictions were made. The matrix can be utilized to determine the classifier's overall performance and identify which classes the classifier was performing well or poorly. Here in this approach, the Glioma AUC value was 100%, the Meningioma AUC value was 99%, the No-Tumours AUC value was 100%, and the Pituitary AUC value was 100%, as shown in (Fig. 11).

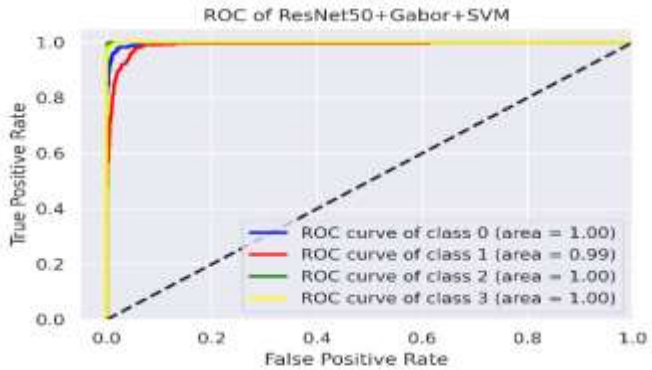

FIGURE 11. ROC Curve of Gabor+ResNet50+SVM

D. QUALITATIVE RESULTS

a). Developed Model Performance Evaluation: The effectiveness of a model can be measured in several ways. These metrics could provide insight into the model's strengths and weaknesses, as well as a guide for future development and improvement. Here, in this research, a close look was given at the accuracy, precision, and F1 score—among other regularly employed evaluation metrics—to determine how well the suggested model performs, which can be shown in (TABLE I).

TABLE I
PERFORMANCE EVALUATION OF THE DEVELOPED MODEL

Approach	**Evaluation Metrics**		
	Accuracy	***Precision***	***F1 Score***
Gabor+SVM	62.30%	58.25%	56.27%
ResNet50+SVM	95.27%	95.35%	95.26%
Gabor+ResNet50+SVM	95.73%	95.90%	95.72%

The third approach showed outstanding performance among all by giving the highest value for accuracy, precision, and f1-score, which were 95.73%, 95.90%, and 95.72%, respectively. These values can also be seen in (Fig. 12).

b). Comparative Evaluation of Related Work: The comparative evaluation with the previous studies was given below (TABLE II), and a detailed explanation of the study was given in the literature review section. This table shows the comparison of two performance metrics (Accuracy and Precision), the model utilized, and the reference.

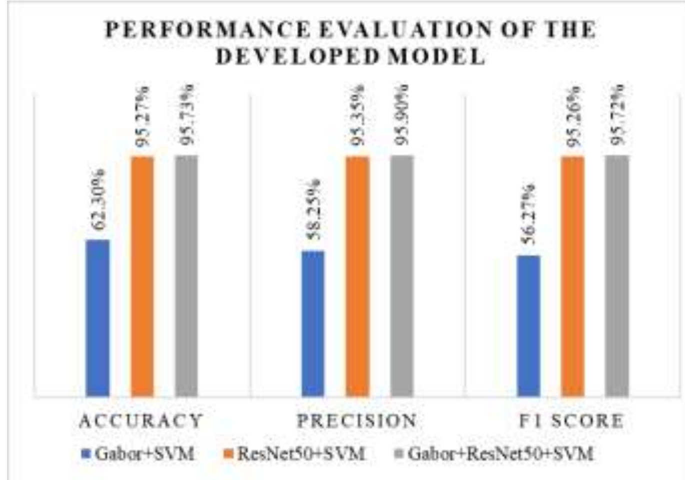

FIGURE 12. Performance Evaluation of the Developed Methodology

TABLE II
COMPARATIVE EVALUATION OF RELATED WORK

Study	**Model**	**Accuracy**	**Precision**
[33]	Fuzzy and Brain-storm Optimization	93.85%	94.77%
[34]	CNN	87%	88%
[35]	BPNN	90%	89%
[36]	Several Pre-Trained DCNN	91.51%	92%
Developed model	Gabor+ResNet50+SVM	95.73%	95.90%

These can also be seen in (Fig. 13).

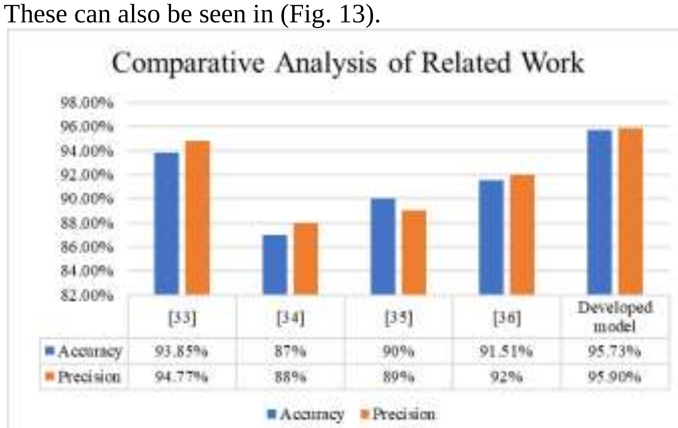

FIGURE 13. Comparative Analysis of Related Work

V. CONCLUSION

Due to the brain's intricate nature, finding a tumour could be extremely difficult. All bodily processes are ultimately under the control of the brain. Early-stage brain tumours could be automatically classified utilizing deep and machine learning approaches. This technology improves patients' chances of survival by facilitating early diagnosis. These methods would assist clinicians in making accurate early diagnoses and treatment decisions. Utilizing a hybrid approach of deep and machine learning algorithms, the suggested methodology in this research intended to classify brain tumours Kaggle MRI images dataset accurately. It was first processed with the Gabor filter to extract features from the MRI images dataset. These obtained features were subsequently classified utilizing the popular and widely utilized MLA technique, Support Vector Machine (SVM). After employing the ResNet50 architecture to extract features, PCA was employed to lessen the dimensionality of the features, and the SVM classifier was utilized to classify the features. In the final method, these features were merged and classified utilizing the support vector machine (SVM) classifier. Several metrics, including accuracy, precision, F1 score, and AUC, were utilized to evaluate the effectiveness of the suggested methodology. The results from combining the Gabor filter and ResNet50 features achieved the best performance with accuracy, precision, and f1-score readings of 95.73%, 95.90%, and 95.72%, respectively. This illustrates how well the suggested algorithm classified MRI images of brain tumours.

VI. FUTURE WORK

The suggested methodology can be further enhanced by combining other image-processing methods and deep learning architectures. It is a versatile design that can be applied to different datasets. The use of this technology in real-time and improving its efficiency for practical use is another crucial area for future research.

FUNDING STATEMENT

The authors declare they have no conflicts of interest to report regarding the present study.

CONFLICTS OF INTEREST

The authors state they have no conflicting interests related to this study.

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