Brain Tumor Prediction from Magnetic Resonance Images

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ABSTRACT

Globally, brain tumours are a leading cause of death. Depending on whether they are malignant or benign, tumours can interfere with neurological and body functions as well as cause severe health problems. Carrying out the diagnosis of brain tumours through the conventional methods of test, such as magnetic resonance imaging (MRI) scan and clinical examination, would be cumbersome and time consuming in most situations. With the latest machine learning hype, deep learning emerged as the medical image analysis game-changer. Early, precise identification of brain tumours has been made possible due to the remarkable performance of convolutional neural networks (CNNs) in extracting fine details from medical images. Support vector machines (SVMs) and CNNs can be combined to improve classification accuracy. The goal of this study is to achieve an improved model for classifying brain tumours using MRI images. This model extracts complex features using a CNN whilst improving classification with an SVM. The resulting model can enhance and speed up medical diagnosis. With a 99.2% training set success rate and a 96.1% test set success rate, the hybrid method is extremely accurate.

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1. INTRODUCTION

The effects of AI and machine learning (ML) have transformed the medical imaging domain, particularly in the detection of brain cancers. Magnetic resonance imaging (MRI) classification and segmentation using complex algorithms allow radiologists to make better treatment decisions and more accurate diagnoses [1]. The ability to evaluate massive amounts of medical data swiftly and accurately has been made feasible by this technical advancement. Brain tumours rank high on the list of the deadliest diseases that humans face today. These tumours can develop in any area of the brain, and patients may not notice any symptom until the disease has progressed significantly. Personality changes, difficulties with memory and communication, hearing or speaking difficulties, persistent migraines and even blindness are common symptoms [2]. Meningiomas, gliomas and pituitary tumours account for about 15%, 45% and 15% of brain tumours, respectively, according to medical statistics. The development of tumours greatly influences the emotional and mental condition of patients due to neural abnormalities, especially those in the brain or spinal cord, which interfere with the normal functioning of the brain [2]. Malignant brain tumours, which include cancer cells, develop rapidly in the brain and spinal cord, unlike benign tumours, which develop slowly, remain localized and do not metastasize. The interference with the normal functioning of the brain due to the development of tumours has a major effect on the psychological condition of patients. From a health standpoint, malignant tumours pose a greater threat [3]. The World Health Organization has divided brain cancer into four grades based on how they grow and behave. Grades one and two are low-grade benign tumours, whereas grades 3 and 4 are high-grade malignant tumours. MRI is the most accurate test for this illness, but computed tomography (CT) and electroencephalography tests can also be used. These tools enable identifying the exact problem area without harming the surrounding healthy tissue [4]. A brain tumour can be examined to analyse the affected cells prior to surgery. Given the relationship between correct diagnosis and therapy success, these procedures are essential for estimating the number of cancer cells [4]. Very recently, doctors have begun using deep learning (DL) algorithms to identify patterns in patients' records. By accurately classifying and simulating brain tumours, the techniques have promised to improve diagnosis accuracy and speed [5]. Though supervised ML algorithms can successfully classify brain tumours, subject matter knowledge utilized in feature extraction and choice plays an essential part in models' performance. Hence, such algorithms can help doctors minimize the interpretation of complicated medical data and speed up the diagnosing process [6]. An early, accurate diagnosis crucial for brain tumours to establish the best treatment and increase the possibility of a good prognosis. When making a diagnosis, tumour grade is more important than tumour kind or stage in deciding on the best course of treatment. This reason explains why CAD systems are so helpful to neurologists; they aid detection, classification and pathological evaluation [7][8]. Traditional brain MRI classification techniques rely on lengthy extraction and geometric operations. Whilst such techniques can identify simple differences in brain imagery, they are not perfect and cannot capture sophisticated patterns. With recent advancements in DL and the widespread use of CNNs for computer vision, CNNs for brain MRI classification have shown promising results [9][10][11]. Due to their ability to acquire hierarchical features from data on their own, CNNs have shown impressive performance in picture categorization tasks. CNNs have also found additional utility in many fields. High-resolution medical images, such as brain MRIs, are best suited for analysis because they can capture local patterns and global context. Support vector machines (SVMs') ability to handle high-dimensional feature spaces with complexity and their unmatched accuracy in multiclass classification tasks have made them increasingly popular in classification problems when used in conjunction with CNNs. The identification of the best hyperplane in a feature space to maximize the separation between classes is the goal of SVMs. The proposed method applies DL and SVM for feature extraction. Features extracted from brain MRI scans are initially trained independently using a CNN. Integration of CNNs with SVMs enables both approaches to be combined for classifying brain MRI images in a dependable, adaptive manner. The research contributions of this approach are as follows:

- This approach draws upon the strengths of both systems. A hybrid model combining a CNN and an SVM is implemented to identify brain tumours. A CNN network extracts deep features from MRI images, and a nonlinear SVM classifier performs the final classification.
- The model's accuracy can be improved by using an SVM as the final layer of a CNN instead. Unlike CNNs that use SoftMax as a classifier, an external classifier such as an SVM reduces overfitting.
- The hybrid model can produce precise results with minimal training data, a significant advantage in medical applications such as diagnosing brain tumours.
- Performance criteria, including precision, recall, accuracy and F1 score, are measured to demonstrate the efficacy of using a CNN with an SVM.

The sections included in this inquiry are as follows: In Section 2, the groundwork is laid in understanding how to use SVMs and neural networks in brain tumour classification, along with the relevant literature. In Section 3, the proposed approach, which includes data processing, model building and the training mechanism, is further developed. In Section 4, the results are presented. In Section 5, the results are compared with recent investigations. In Section 6, conclusions and prospective research are discussed.

2. Related Work

Medical imaging technologies have greatly enhanced early diagnosis, follow-up and detection of illnesses that effect the nervous system, including Alzheimer's disease and brain tumours. In brain scans, ML and DL methods have been applied to mitigate concerns about safety and confidentiality. Hybrid models, characteristic architectures and relation studies are being developed to enhance accuracy and efficiency. Delicate brain MRI images, as part of sensitive patient data, require encryption and secure methods to ensure confidentiality. Using transfer learning, CNN methods and hybrid models, this review summarizes the research on brain picture categorization for the diagnosis of brain tumours and Alzheimer's disease. This work also reviews the literature on medical image encryption and steganography techniques applied to MRI data.

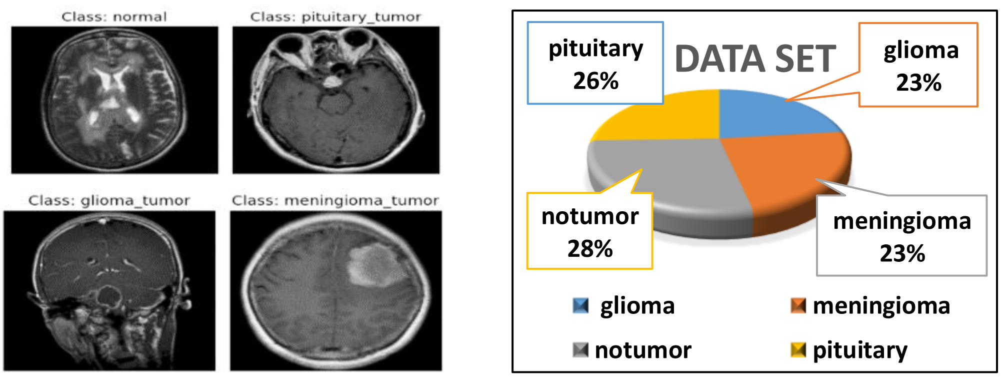
Kutlu et al. [12] proposed a new medical imaging approach for liver and brain tumour diagnosis and classification. Their method utilizes CNN, discrete wavelet transform (DWT) and long short-term memory (LSTM) networks to classify liver tumour CT images as benign or malignant. Using two datasets, the composite technique, which combines CNN, DWT and LSTM networks, achieved classification accuracies of 99.1% for liver cancers and 98.6% for brain tumours. In a similar context, Yildirim et al. [13] introduced a hybrid method for diagnosing Alzheimer's disease using CNN architectures. The model is divided into four distinct stages, each corresponding to a degree of disease progression. The ResNet50 methodology serves as the foundational framework. The results obtained independently with AlexNet, ResNet50, DenseNet201, VGG16 and the hybrid methodology indicate that the model achieved 90% accuracy, surpassing the performance of other CNN architectures and yielding even better results. Furthermore, in [14], Mohammed et al. assessed ML methods for dementia and Alzheimer's disease using the OASIS dataset. Amongst the models assessed were CNNs such as AlexNet and ResNet-50, as well as hybrid approaches that combined ML and DL techniques. The hybrid model, which combined AlexNet with an SVM, demonstrated outstanding performance and achieved 94.8% accuracy with impressive AUC, sensitivity and specificity scores. Similarly, Huang et al. [15] proposed a 3D CNN and SVM network model to address issues in binary classification. This model incorporated a CNN with SVMs to segment the problem into three binary classes. The output of all such networks was integrated into a result for categorization. Learning was utilised, where CNNs with SVMs were trained, and the results were fused using a decision fusion method. Apart from these studies, Abunadi [16] discussed four other systems for monitoring Alzheimer's disease progress. The first system used artificial neural networks (ANNs), including feedforward neural networks, as classifiers. The next system used pretrained DL classifiers, that is ResNet-18 and AlexNet. The third system was a combination model that combined ResNet-18 and AlexNet for feature extraction and later ML classification of the resulting feature maps. The fourth model used ANNs and FFNNs, combining the hybrid characteristics of the ResNet-18 and AlexNet models. The FFNN algorithms produced remarkable results, including 99.8% accuracy, 99.9% precision, 99.75% sensitivity, 100% specificity and an AUC of 99.94%. In addition, Agarwal et al. [17] proposed a DCNN-based hybrid diagnostic system to categorize MRI images into four classes: normal, meningioma, pituitary tumour and glioma. The system combined CNN with various classification methods such as decision tree, naive Bayes, AdaBoost, K-Nearest Neighbour (KNN) and SVM. The hybrid CNN-KNN system achieved 99.59% accuracy, whereas the CNN-SVM system achieved 99.51%. Lastly, Shanjida et al. [18] proposed a lightweight deep CNN for feature selection in brain tumour classification. The method followed three main stages: preprocessing, feature extraction and classification. A modified CNN was employed for feature extraction, whereas K-fold cross-validation and data augmentation were used during preprocessing. Finally, an SVM was applied to categorize brain cancer from MRI data, reaching a level of precision of 96.7%.

3. METHOD PROPOSED

This section explains the phases of the proposed method, including dataset selection, preprocessing methods, data segmentation, the techniques used, the resulting outputs and the evaluation metrics.

3.1 Dataset Description

The study used a publicly available dataset of BT of various sizes. The Kaggle platform provided the BT dataset [19]. Each strategy used a dataset that included (5,712) MRIs, which were further separated into four groups: pituitary tumours (1,457), meningioma (1,339), no tumour (1,595) and glioma (1,321), with different sizes. Figure 1. (a) shows the categories in the dataset and (b) the proportion of each category in the dataset.



(a) (b)

Figure1. (a) Data set classes and (b) Proportion of images in each class

3.2 Dataset Preprocessing

Several methods used during the preprocessing phase of the dataset include the following: Resize: Image sizes are reduced to 150×150 pixels for uniform pixel count to decrease complexity and minimize training times. When attributes are normalized, their pixel values are rescaled from [0, 255] to [0, 1] with a standard deviation of 0, which improves the model's performance. Shuffling: Data are presented in a random sequence that reduces biases and patterns and makes models more general.

3.4 Data Augmentation

The process of incorporating unique, trainable data is called data augmentation and is used to improve the efficiency of ML algorithms. This step involves creating modified images using rotation, transformation and reflection to reduce overfitting, improve accuracy and generate corrected random images with appropriate distortions. Tables 1 and 2 detail the data augmentation procedure and dataset partitioning before and after augmentation, respectively.

Table 1: Data augmentation process settings

Transformation	Setting
Rotation	Rotation by 30 degrees
Width shift	Shift the image horizontally by up to 30%
height shift	Shift the image vertically by up to 30%
Zoom	30 degrees
Horizontal flip	Image horizontal flip around the axis

Table 2: Dataset partition after augmentation

Class	Total Data	Before Augmentation		After Augmentation	
		Train Data	Test Data	Train Data	Test Data
Glioma	1321	1060	261	1684	261
Meningioma	1339	1072	267	1624	267
No Tumour	1595	1279	316	1975	316
Pituitary	1457	1158	299	1846	299
Total Data	5712	4569	1143	7129	1143

3.5 Proposed Method: Hybrid CNN-SVM Model

The proposed method describes extracting features from a CNN and classifying them with an SVM. In the first stage of this technique, a CNN model is tailored and trained from scratch. In the second stage, the CNN classification layer is removed and replaced with an SVM brain tumour classification model. Data augmentation is added to the training data.

3.5.1 Hybrid CNN with SVM Model

The SVM classifier is effective for classification but requires methods for extracting image features. This method proposes using DL models to extract features from images. The CNN extracts features from images, and the SVM calculates the images based on those features. Combining these two methods produces a hybrid model. Figure 3. illustrates the proposed hybrid model. The components of the CNN and SVM are detailed below:

A. CNN Model

The 2D convolutional network extracts features from images. In this strategy, the four different kinds of brain tumours' MRI images are used to train a CNN initialized from scratch. The network consists of the following layers:

- The network uses 5 convolutional layers with filter sizes of 3×3, numbers of filters (16, 32, 64, 64 and 128), and a ReLU activation function to capture complex features. These layers allow the model to learn features

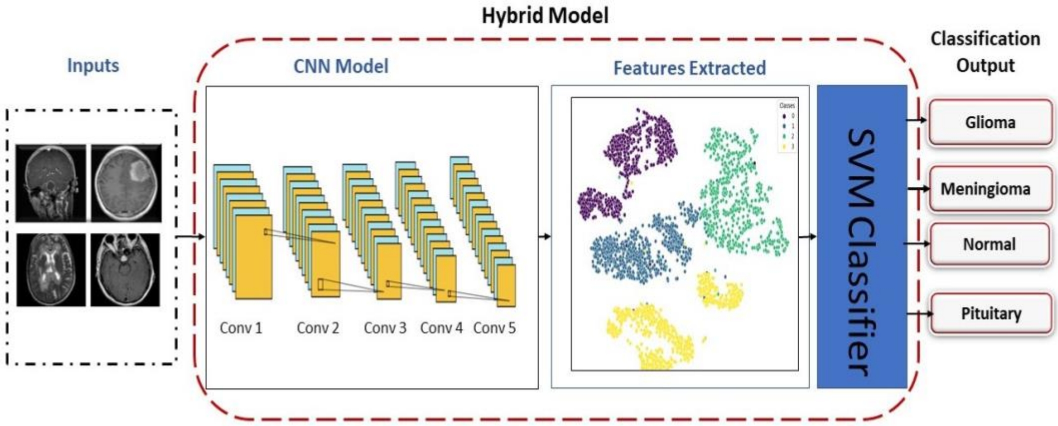


Figure 3. Hybrid CNN with SVM model framework

- Batch normalization layer: After each convolutional layer, batch normalization is implemented to standardize the activations and maintain the mean output near 0 and the standard deviation near 1. This approach speeds up training and stabilizes the model.
- After the second convolutional layer, the model is trained with MaxPooling layers to improve computational efficiency and reduce spatial dimensions whilst preserving the most critical information.
- Dropout layer: A dropout layer with a depth of 0.25 follows each convolutional layer. A random portion of neurons is dropped or ignored in each batch during training. This approach prevents the model from relying solely on any single neuron and reduces overfitting.
- Flattening layer: This layer is used after the fifth convolutional layer and flattens the feature maps from the previous layer into a single dimension.
- Dense layer: Two dense layers containing 128 and 256 neurons are applied with the ReLU activation function that learns complex relationships. Regularization is added to the first dense layer, L2 (0.01), to prevent overfitting.
- Output layer: A dense layer consisting of 4 neurons is used with a SoftMax activation function to classify brain tumours into four categories.

B.SVM CLASSIFIER

SVM is a supervised learning algorithm used for classification that creates decision boundaries to separate features into multiple classes. The SVM classifier consists of the following:

- The classifier is built using a nonlinear function, a radial basis function kernel. It maps the input data into higher-dimensional spaces. It can separate data that cannot be linearly separated and allow for more complex decision boundaries.
- A multiclass classification case is used where one-versus-the-rest techniques are used. Where the desired class is treated positively, and the rest of the classes are treated negatively.
- Cross-entropy loss is used with the SVM to evaluate the classification model. Cross-entropy measures the difference between the true labels of the training and test data and the SVM's predicted probabilities for each class of the training samples.
-

3.6 TRAINING

The dataset utilized to train the CNN model consisted of (7,129) images. The process used a batch size of 32 and epochs of 100 with an Adam optimizer and learning rate of 0.0001. The model learned complex patterns and feature representations from the images. The final classification layer, which contained the SoftMax activation function, was removed to serve as a feature extractor. The SVM classifier was fed features generated by the trained model from the training and test data. The SVM classifier underwent its paces on the test data after being trained on features collected from the training data. The training parameters are shown in Table 3, and the specific parameters used to train the SVM are listed in Table 4. A brief overview of the CNN model is presented in Table 5.

Table 3: Hyperparameter of the tailored CNN model

Hyperparameter	CNN Model
Activation function	ReLU
Learning rate	0.0001
Optimizer	ADAM
Loss function	Categorical- Cross Entropy
Batch size	32
Data size	150×150
Dropout rate	0.25
Regularizer L2	0.01
Epochs	100
Classifier	SoftMax

Table 4: SVM Parameters

Parameter	SVM Model
function	RPF
Loss function	Cross entropy loss
SVM type	Multiclass
Decision function shape	One-vs-Rest
Solver	Nonlinear

Table 5: Model summary of the CNN model

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 148, 148, 16)	160
batch_normalization (BatchNormalization)	(None, 148, 148, 16)	64
dropout (Dropout)	(None, 148, 148, 16)	0
conv2d_1 (Conv2D)	(None, 146, 146, 32)	4,640
batch_normalization_1 (BatchNormalization)	(None, 146, 146, 32)	128
max_pooling2d		
(MaxPooling2D)	(None, 73, 73, 32)	0
dropout_1 (Dropout)	(None, 73, 73, 32)	0
conv2d_2 (Conv2D)	(None, 71, 71, 64)	18,496
batch_normalization_2 (BatchNormalization)	(None, 71, 71, 64)	256
max_pooling2d_1 (MaxPooling2D)	(None, 35, 35, 64)	0
dropout_2 (Dropout)	(None, 35, 35, 64)	0
conv2d_3 (Conv2D)	(None, 33, 33, 64)	36,928
batch_normalization_3 (BatchNormalization)	(None, 33, 33, 64)	256
max_pooling2d_2 (MaxPooling2D)	(None, 16, 16, 64)	0
dropout_3 (Dropout)	(None, 16, 16, 64)	0
conv2d_4 (Conv2D)	(None, 14, 14, 128)	73,856
batch_normalization_4 (BatchNormalization)	(None, 14, 14, 128)	512
max_pooling2d_3 (MaxPooling2D)	(None, 7, 7, 128)	0
dropout_4 (Dropout)	(None, 7, 7, 128)	0
flatten (Flatten)	(None, 6272)	0
dense (Dense)	(None, 128)	802,944
dropout_5 (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 256)	33,024
Total params: 972,292 (3.71 MB)		

Trainable params: 971,684 (3.71 MB)
Non-trainable params: 608 (2.38 KB)

4. Discussion and Results

To assess the effectiveness of the proposed model, which combines the capabilities of CNNs and SVMs, a set of criteria is often used in medical image classification. These criteria help assess the model's efficacy, accuracy and ability to differentiate between different types of brain cancer. The criteria can be summarized as follows [20][21][22][23]:

1. **Confusion Matrix:** An N × N square matrix used in binary and multiclass classification shows the predicted and actual frequencies of occurrence of each class. The matrix shows a classifier that makes incorrect and correct predictions in classification tasks. The confusion matrix helps determine the classifier's performance, strengths and weaknesses and the best way to improve the model. Predictions might be correct or wrong [20]. True negative (TN), an entire set of healthy images, is considered normal. True positives (TP) means that abnormal photos are correctly detected as harmful. In the case of false positives (FP), normal images are mistakenly labelled as abnormal. Unhealthy images are characterized as normal, a phenomenon known as false negatives (FN).
2. **Accuracy:** Accuracy is the percentage of dataset samples that are successfully classified. Good results are those that are above 80%, whereas exceptional results are those that are above 90% [20].

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

3. **Recall:** The actual model's sensitivity score is used to identify positive cases, which are then classified, and scores between 70% and 90% are acceptable [20].

$$Recall = \frac{TP}{TP+FN} \quad (2)$$

4. **Precision:** When the number of samples that are correctly classified is compared with the number of relevant events, an accuracy rate of more than 80% is normally considered excellent quality [20].

$$Precision = \frac{TP}{TP+FP} \quad (3)$$

F1 score: F1 score is a comprehensive measure of performance that balances precision and recall [20].

5. $$F1 - score = \frac{2TP}{2TP+FP+FN} \quad (4)$$

4.1 Evaluation of the Result

The performance of the hybrid model is shown in the study, together with the performance of the standard CNN model, where the CNN model and the hybrid model were trained for 100 epochs with a batch size of 32. The accuracy of the model in training was 98.9%, with a loss of 0.1. This section delineates the outcomes of the composite model that integrated CNN with SVM. Following CNN training, the final layer intended for classification was removed. The features extracted from the CNN were then utilized as inputs for the SVM to execute classification. Improving the SVM algorithm's ability to detect BT is the goal of this hybrid model by employing the features extracted from deep CNN models. Following the SVM training with the extracted features, the hybrid model achieved a training accuracy of 99.2% and a testing accuracy of (96.15%). Table 6 delineates the performance metrics achieved by the hybrid model. Table 7 presents the classification report. Figure. 4 shows the classification report of hybrid CNN with the SVM model.

Table 6: Performance evaluation of a hybrid CNN with SVM model

Model	Evaluation Metrics						
	Train AC%	Test AC%	Train Loss	Test Loss	F1 score%	Precision%	Recall%
CNN+SVM	99.2	96.15	0.03	0.1	96.14	96.14	96.15

Table 7: Classification report of a hybrid CNN with SVM model

Class	Precision%	Recall%	F1 score%	Support
glioma	0.96	0.95	0.96	261
meningioma	0.93	0.92	0.92	267
no tumour	0.97	0.99	0.98	316
pituitary	0.98	0.98	0.98	299
accuracy		0.96		1143
macro avg	0.96	0.96	0.96	1143
weighted avg	0.96	0.96	0.96	1143

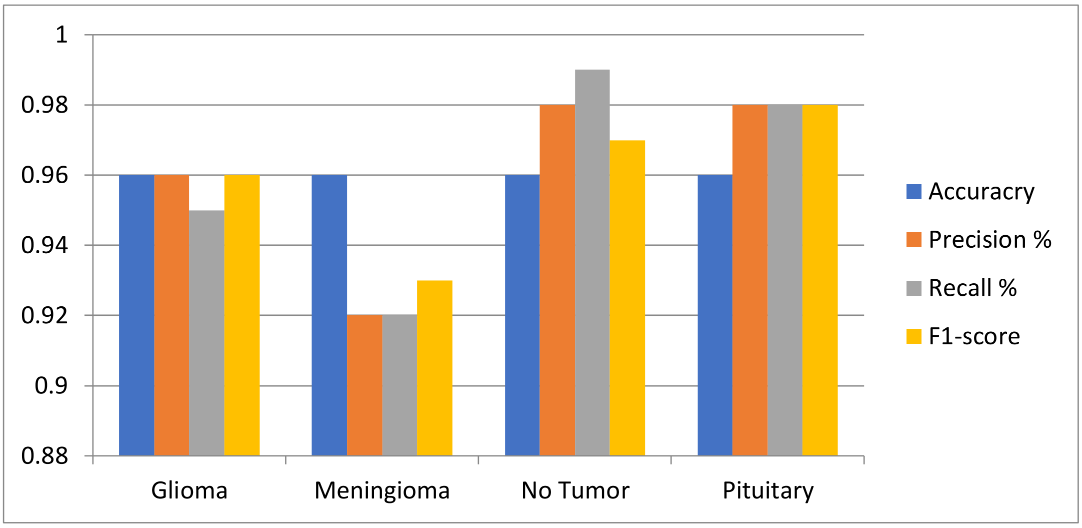


Figure 4: Classification report of a hybrid CNN with SVM model

Table 6 demonstrates the performance of the CNN-SVM hybrid model. This model has an accuracy rate of 99.2% on the training data, with a loss of 0.03. This outcome implies that the model can classify 99.2% of the data in the training set correctly, and the predicted values are almost identical with the actual values. The resulting accuracy from the test data was 96.15%, with a loss of 0.1 by using the hybrid model. This result implies that the model can correctly classify 96.15% of the data in the test set, and the model can deal with unseen data. The loss on the test data is slightly higher than the loss on the training data, but it is still low; hence, the model can deal with unseen data. The F1 score is 96.14%, and the precision and recall are both 96.14%–96.15%. This finding implies that the model can effectively deal with TPs effectively and ensure that the FPs and FNs are kept at manageable levels. Table 7 displays the classification results of the hybrid model in four different brain MRI classes. The results include accuracy, precision, recall and F1 score. The results show the strengths and weaknesses of the hybrid model in classifying glioma, meningioma, no tumour and pituitary tumour classes. Precision values: glioma 0.96, meningioma 0.93, no tumour 0.97 and pituitary tumour 0.98. Recall values: glioma 0.95, meningioma 0.92, no tumour 0.99, pituitary tumour 0.98. This result means that the hybrid model can classify real glioma cases with 95%, real meningioma cases with 92%, no tumour classes with 99% and pituitary tumour classes with 98% precision. F1 score: The hybrid model's precision and recall rates are high in all four classes. This outcome shows that the hybrid model can classify glioma, meningioma, no tumour and pituitary tumour classes well. The hybrid model has an overall accuracy of 96%. The hybrid model can classify most classes of tumours correctly with very few FPs and FNs. Macro average and weighted average: The hybrid model's performance can be calculated using the macro average and weighted average of the classes. The macro average is useful when the dataset is unbalanced. The macro average calculates the average of precision, recall and F1 score of the classes. The weighted average considers the prevalence of the classes. All categories contribute equally to the average. The macro average ratio of (0.96) demonstrates the hybrid model's effective performance across all categories on average. The weighted average considers the sample size within each category when calculating the average. A category with more samples exerts a greater influence on the final average, with a weighted average of 0.96. The hybrid model performs well in every category after considering imbalances. The confusion matrix measure is illustrated in Figure 5.

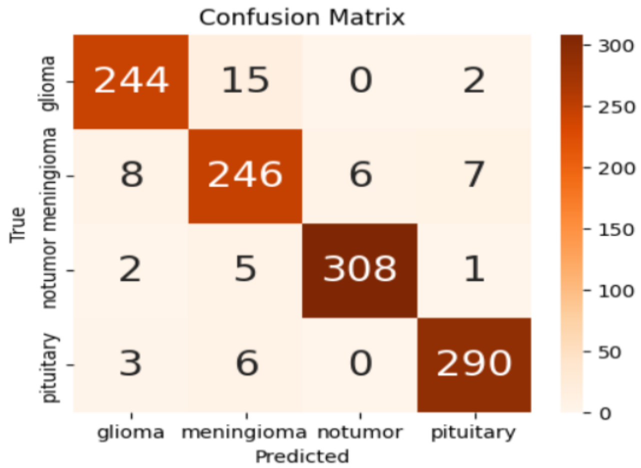


Figure 5. Confusion matrix of hybrid CNN with the SVM model

In Fig. 5, the confusion matrix delineates the counts of TPs, TNs, FPs and FN for four cases of brain tumours. The hybrid model accurately predicted the following true positives: (244) for glioma, (246) for meningioma, (308) for cases with no tumour and (290) for pituitary tumours.

5. Comparison with Previous Works

In this section, the effectiveness of the proposed CNN with SVM hybrid model is evaluated through analysing the comparison with other studies, and the model's importance in classification is demonstrated. Table 8 shows a comparison with other recent works.

Table 8: Comparison of the hybrid model with other recent models

Studies	Methods	Dataset size	Class	Accuracy %
[24]	CNN (5 CONV layer) + SVM (Linear)	2957	3 class	96
[25]	ResNet50+SVM	7023	4 class	95.7
Proposed model (CNN+SVM)	CNN (5 CONV layer) + SVM (Nonlinear)	5712	4 class	96.15

Table 8 compares the proposed hybrid model with other works. Compared with research [24], the hybrid study model achieved an accuracy comparable with that of the model in the study [21], with differences in data size, classification quality and number of classification categories. The proposed hybrid model uses nonlinear classification because can better approximate the decision boundary and the relationships in the data. By contrast, in study [24], a linear SVM was used because the data were assumed linearly separable. Our hybrid model has a significantly larger dataset than in study [24] because more data improves generalization. However, at a certain point, not enough data are available, and this results in overgeneralization.

Brain tumours can be classified into four types using the hybrid model, which is a more complex case compared with the study [24] that classifies the tumour into three types. Compared with the study in [25], the hybrid model can achieve a higher level of accuracy. Our hybrid model uses a CNN with five convolutional layers to perform feature extraction, followed by an SVM classifier to make the final decision. Study [25], by contrast, uses ResNet50 to perform feature extraction and then a separate SVM to make the final decision. Despite having a simpler structure, the hybrid model can achieve a more advanced level of accuracy compared with the study [25], reaching 96.15%. The most important differentiating factor is the use of a nonlinear SVM classifier in hybrid model, which allows for better handling of data that is not linearly separable. This result suggests that integrating CNNs with nonlinear SVMs is particularly efficacious.

6. CONCLUSION

The method involves training the CNN algorithm on a training set and running the algorithm. An input to the SVM classifier is made up of the features that were derived. In medical settings, the method has been effective in identifying brain malignancies. The combined model attained a high percentage of 99.2% accuracy when trained on the training set and 96.1% when assessed on the test set. The approach addresses the complexity of medical images, and this ultimately results in an accurate diagnosis. Substantial performance gains for the combination of CNN and SVM result in a 96.15% accuracy. Contemporary feature extraction methods such as CNN convolutional layers can greatly improve classification accuracy. Despite promising results in brain tumour classification with the suggested CNN and SVM model, multiple paths for future improvement remain. Processing 3D MRI data to obtain more inclusive spatial information is one direction to increase the capability of the model. The model could add the patient's age, symptoms, genetic background and photos to increase accuracy and interpretation further. Potentially mobile-enabled or real-time diagnostic solutions can be built. The model can be assessed on several databases to ensure it works with various kinds of data. Applying ensemble learning to the model could further improve its performance.

AVAILABILITY OF DATA AND MATERIAL

The brain tumour MRI dataset analysed during the current study is publicly available on Kaggle at https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset (accessed June 2024)

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