2024 International Conference on Communication, Computer Sciences and Engineering (IC3SE)

Brain Tumour Detection Using MRI Images and CNN Architecture

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2024 International Conference on Communication, Computer Sciences and Engineering (IC3SE) | 979-8-3503-6684-6/24/$31.00 ©2024 IEEE | DOI: 10.1109/IC3SE62002.2024.10593571

***Abstract*–The brain tumour is a phenomenon involving the creation of cells which multiply within the brain and they are different from the normal cells. Among all platforms, magnetic resonance imaging (MRI) has the highest level of accuracy in finding these brain cancer cells. Magnetic resonance imaging or MRI has made it possible to visualise tissues closely and then the diagnosis can be made. The result of an MRI scan will help in detecting the presence of a brain tumour or determining that there isn't a tumour. In the past few year's algorithms like deep learning and machine learning driven by AI have improved computer-aided image analysis tools which can now achieve the sensitivity of top radiologists. By modernising the diagnostic systems, the speed of tumour detection and error rate can be boosted which both play an essential role in a successful cancer treatment. This, in turn, lowers the possibility of healthcare providers misdiagnosing the patient and supports them in the right purposeful treatment. Here we have a research application where a convolutional neural network (CNN) discriminates brain tumour images compared to others and its implementation is carefully presented. The primary objective of this research is to employ Convolutional Neural Networks (CNN) as a machine learning technique to facilitate the detection and classification of brain tumours. However, the performance of the untrained and pre- trained CNN manifests through a precision of 95% and classification accuracy rate for training and testing respectively. Hence, such data provide the strongest evidence that in the situation of brain tumour prognosis, CNN is the most important instrument.**

***Keywords* – Machine Learning, Brain tumour, MRI images, Dataset, Convolutional neural network (CNN), Confusion Matrix, Loss function**

I. INTRODUCTION

Brain tumours are one of the major brain degeneration diseases where the tissues have grown abnormally. In this phase, most of the time, small lumps or tumours known as the abnormal tissues develop inside some parts of the brain, resulting from the over-growth of the brain cells that are already abnormal or that are damaged as a result, and this brings about grouping of some cells at some places in the brain's tissue. The imaging scanning, MR in this case, along with the radiologist's evaluation will serve as the foundation of brain tumour diagnostics which is only done by hand and requires the expertise of a trained specialist to identify the tumour. MR image' a result of high density, presents a special resolution for higher tissue fields' examination. In opposite, the MRI techniques bear higher security levels as

well as high sensitivity in producing the actual image of the brain. So, the brain images resulting from the MRI are clear as well as successful. On the contrary, MRI scans with higher resolution contain information on very detailed structures of the brain such as the layers and the types of tissue. Advanced scanning and imaging would be much more efficient because of having so many good reasons. These MRI scans typically employ four standard sequences: Observing T1-weighted MRI (T1), T2-weighted MRI (T2), T1-weighted compare- improved MRI (T1-CE), and FLAIR will serve as our diagnostic sequence. Nonetheless, T1 weighted compare- improved MRI is considered the main method since it offers a great ability to shape into success and is also more clearly able to differentiate between normal nab pathological tissues. We have here the compilation of quite a large volume of data that comes from MRI scans and a big number of data is fitted in making available the diagnostic and therapeutic processes of brain oedema.

Deep learning, a sophisticated form of artificial intelligence, originates from machine learning principles. Unlike traditional programming that follows predefined rules, deep learning enables machines to self-learn through networks of artificial neurons mimicking the human brain. This technology has shown exceptional performance in tasks such as medical face mask screening and image description. Its application in medical image classification, detection, and segmentation is highly recommended. Deep learning techniques have been successfully used to detect various diseases, including breast cancer, Parkinson's disease, COVID-19, heart conditions, and diabetes, as well as for medical image segmentation. The advancement of AI has given rise to numerous specialized scientific fields.

A convolutional neural network (CNN) is a type of deep neural network that is highly effective in addressing image classification and segmentation tasks. It stands out as one of the most widely used deep learning models today. In stages, each layer plays a unique role such as convolutional, pooling, fully connected, and dropout ones, and the

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structure can extract complex patterns and provide good prediction. Deep learning strategies especially applied in CNN (convolutional neural networks) provide amazingly comparable outcomes to radiologists' accuracy. This fact alone explains why CNNs are so important for the future of medical image analysis because these methods result in highly precise and quick solutions for many important tasks such as classification and segmentation.

In the last years, Convolutional Neural Networks (CNNs) have been used as an efficient method for medical image segmentation which involved ground-breaking and added value contribution of diagnostic tools. Unlike the regular methods, the basic architecture of CNN enables it to achieve the same result in a much faster way with lots of features able to be discovered directly from the linked image. Among the CNNs that have been extensively used in computer vision, especially in the medical imaging area where high resolution and fine detail extraction are essential, CNNs are the dominant and most popular category. The accuracy of finding main features has made algorithms based on CNN widely used and prominent in leader boards of image understanding problems, including the Brain Tumour Segmentation (BRATS), as well as information processing in medical imaging (MICCAI), and two conferences: The International Symposium on Biomedical Imaging and Information Processing for Medical Imaging highlights the significant potential of convolutional neural networks (CNNs) in diagnosing brain tumours. This complex and demanding field illustrates the necessity for sophisticated and robust techniques capable of handling the intricate tasks involved in medical image analysis.

The structure of this paper is as follows: In Part II, a clear synthesis of relevant research literature is presented. In Part III, we will delve into the methodology of our research and the implementation of machine learning algorithms. In Part IV, all the techniques of performance evaluation are explained in detail. Part V presents the results and discusses them. Finally, Part VI offers a concluding analysis and recommendations for further studies.

II. Literature Review

Recent research on brain tumour segmentation has explored two primary divisions of machine learning techniques: unsupervised learning and supervised learning. In supervised learning, humans first provide the correct labels on the information, then the artificial intelligence model studies from these labels to make better predictions on future data and improve results. It is by this process that the model will be able to dig deeper into the patterns and features of the data and thus have its segmentation improve over time.

In segmentation using unsupervised technique, it requires person validation of output variables, they are still very much dependent on the algorithms used. Techniques like – the Fuzzy Clustering method and, Support Vector Machine (SVM) method are generally utilized in this technique. However these methods have shown good results in identifying or detecting tumours yet, they struggle when normal tissues and tumour tissue borders become unclear. Furthermore, the procedure can be slow given that the AI algorithm is required to extract details and features from plenty of information.

The segmentation process, which is another important and difficult part of the current computer-aided tools, is a significant consideration and these are extremely beneficial to medical practices. Up to now, it was brain tumour segmentation used to be a process that depended on human input and that was very time-consuming, experienced people oriented and required much effort and attention. Essentially, the entropy-based segmentation mechanism is useful because it would make the diagnosis a matter of difficulty and allow the diagnosis not to be a subject of a different interpretation. To achieve this, it is anticipated that the MRI's precision will also be enhanced for brain tumour diagnosis and treatment.

Unlike other machine learning techniques, CNNs offer an element of automation by allowing these segmentation and feature extraction processes to be masked from experts' interference. Automation in this part of the process ensures that it is accurate in comparing and contrasting details from the image. Detailing is a core part of image analysis. While CNNs have to learn a large number of these parameters which hence requires vast computational resources such as GPUs; these GPUs are needed because of the intensified computation needed; during training. The CNN network performs two primary tasks: is to do with classifier and feature extraction. The pooling and convolution layers are accountable for the implementation of extracting feature. While the data is getting classified- the fully connected layers are assisting. In [21], a CNN architecture was demonstrated for tumour detection and classification, the results from which allowed in finding the best appropriate model to use for this classification. Our first model had only one convolutional layer, but the two-layer model was the second model. The results showed that the more convolutional layers we had led to better model performance. Out of the 93% accuracy that a single model reached and a loss value equal to 0.23, there was already a piece of evidence that convolutional neural networks can be helpful in the analysis of medical images.

For the methods found within artificial neural networks, one that stands out as a useful approach is transfer learning. The premise is straightforward: even though training a new CNN architecture from scratch would be reasonable, instead, architectures trained on big datasets with consistently demonstrated performance are reused. This approach makes it possible to have one or several transfer learning models adjusted accordingly to the demands of the specific task and the kinds of features to be detected or categorized. Transfer learning enjoys the exciting opportunity to utilize the domain's shared experience and boost the model efficiency to address many use cases.

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In contrast to rule-based concepts that require substantial expert input, today's CNN technologies empower themselves to self-teach by themselves. The concept of weight-sharing techniques permits the formation of resilient networks which are capable of automatically establishing tumours from MRI images. This method provides to simplify the training process and at the same time improves the model's precision and promptness in medical image analysis tasks.

In a study published by [24], the objective was to enhance accuracy through the implementation of transfer learning strategies using three pre-trained CNN models: VGG19, Inception V3, and MobileNet V2. Researchers obtained high accuracy of 88.22%, 91%, and 92% as performance measures. Therefore, the MobileNet V2 model is more efficient as it gives better results than the other two models.

In another study, presented in an article [25] as a solution to distinguishing benign from malignant tumours with an approach based on Artificial Neural Networks (ANN), the images were firstly processed with filters, and then a technique based on the average colour moment for the extraction of features was applied." Second, those map projected data were transferred to ANN for classification resulting in an accuracy rate of 91.8%.

In [26], a paper has detailed a model that has been built based on the histogram statistical equalization technique. This is achieved by moving every pixel of the image after calculating statistical features like average sum, variance, entropy and dissimilarity. The method was specially devised to differentiate high-grade and low-grade classes of the magnetic resonance images of cervical glioma. Hence, the application of this strategy produced 80.88% sensitivity, 83.6% accuracy, and 86.84% specificity.

Another approach in image feature extraction involves combining deep learning concepts, specifically CNNs, with various preprocessing techniques. These techniques encompass data augmentation, edge detection, genetic algorithms (GA), discrete wavelet transform (DWT), and principal component analysis (PCA). Researchers in [37] paper examined a combination of augmented data and outline edge approaches. Data augmentation, through the production of additional images from the previous ones, helps in acquiring the larger data size, while the edge detection technique, which is responsible for marking the ROI, is applied. Then process of feature extraction is finally performed using a simple CNN model. Incredibly, the adoption of this dual strategy led to an accuracy of 88% identification.

TABLE I. SUMMARY OF SOME RELATED WORKS

Study	Dataset	Processing technique	Classifier	Result
[21]	Kaggle Dataset	Data Augmentation	CNN	Ac=93% Loss = 0.23
[24]	Brain Tumour Dataset	Transfer learning	VGG19	Ac=87% F1score=87.16%
			Inception	V3 Ac=90% F1score=89.97%
			MobileNet V2	Ac=87% F1score=87.16%
[25]	Harvard Medical School Website Dataset	Noise Filtering Average colour Moment	ANN	Ac=91.8%
[26]	LGG Flair MRI images	ROI feature extraction	Random forest	Ac=82.5% Sensitivity=81.7% Specificity=85.7%

Table I categorizes the outcomes of these searches, detailing the classification model, the selected preprocessing technique, and the scores achieved according to the metrics employed in each study.

III. METHODOLOGY

A. *Comprehensive Summary of the Suggested Detection Framework*

Effective image classification with machine learning techniques, such as conventional neural networks, requires following a series of sequential steps: data abstraction, data preparation, feature identification, classification, and learning. Consistent with standard machine learning procedures, we initiated our process by collecting data from the collection of brain MRI images accessible via Kaggle. This dataset consists of 2200 MRI images divided into two categories of Yes and No tumour labels, corresponding to the cases where the tumour is present or not. When we got to the question of developing our CNN architecture, some factors were consulted that mainly have to do with the specific limitations of our case. On the other hand, the discipline of medical imaging could hardly use the rich data because of privacy concerns, which led to the exploration of techniques like data augmentation to enrich the dataset. Then we examined the technological issues in detail. In particular, we avoided such complex transformations and were able to combine learning with enjoying consequently. The results of existing research indicate that the more basic transformations tend to be more effective because the noisy features that hinder effective learning may be introduced by the complex transformations.

In the data pre-processing phase, methods like image partitioning and size normalization are utilized. After this, the CNN model is constructed and utilized as a tool for detecting brain tumours. Following that, the dataset is divided into training, validation, and testing subsets. Once the model is defined and compiled, an evaluation metrics approach is set up to gauge its effectiveness. Ultimately, predictions are produced by running the model on MRI images. Figure 1 showcases the architecture of the CNN model employed in our study, accompanied by

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comprehensive explanations of layer definitions and functions detailed in Subsection C.

B. Dataset Collection and Pre-processing

This part explains the dataset that is being used, which has been sourced from a publicly accessible Kaggle database. The database comprises three folders: one containing 1200 MRI scans depicting brain tumours, another folder including 1000 MRI scans of normal brains, as well as a folder intended for testing that remained unused due to an alternative approach to testing data. As a result, the final database designed has only two folders that consist of 2200 images - 1200 with tumours and 1000 without. Figure 2 shows the sample pictures from the dataset.

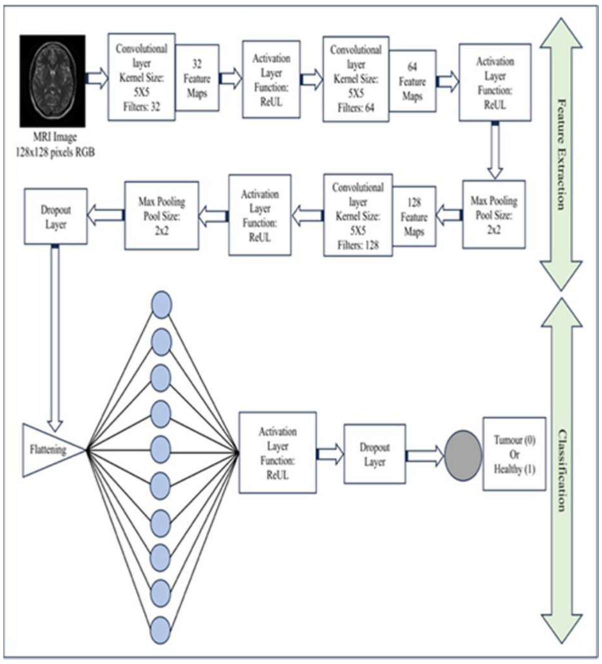

Figure 1. CNN Architecture

Since MRI images can catch the visualization defects that limit the quality of the images and cause distortion and resolution issues, several pre-processing techniques are used to increase the stability and usefulness of neural network analysis. Common approaches contain among them standardizing size of the image, reducing dimensionality and augmenting data. The images are adjusted to a resized dimension (128, 128, 3) (width, height, channels) for easier adaptability to the learning process.

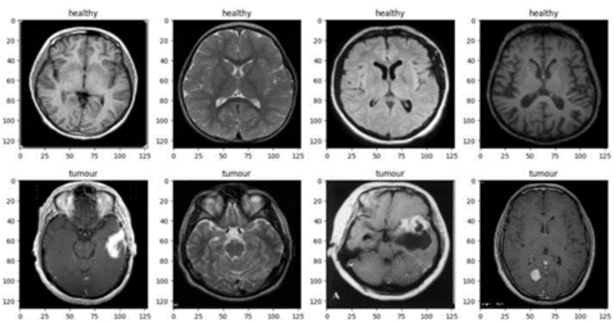

Figure 2. Samples Images for Brain Tumour Dataset.

The first pre-processing step is wrapping and cropping, which is responsible for the removal of undesirable outer regions and outer peripheral areas from the images. Subsequently, the dataset is divided into training, testing, and validation sets, allocated in an 80:10:10 ratio. In particular, the dataset comprising 2200 images is divided into training, testing, and validation sets, with 1760, 220, and 220 images, respectively. All pictures undergo the processing and forming of an array. The last piece of this process is called coding, where the labelled data is numerically coded for easy interpretation and analysis. Figure 3 depicts the model constructed based on preprocessing input images and the CNN algorithm's operation to classify unhealthy and healthy brains.

C. Classification Using Machine Learning Algorithms

Distinction of brain tumours is within the scope of classification algorithms, one substantial contribution to imaging analytics, feature extraction, and various applications. To accomplish the task of a good categorization, the CNN model is utilized with the role of input feature taking from every image into consideration and the separation between given images is also possible. According to the suggested architecture of CNN, there are several layers in the model, consisting of three Convolutional layers, three Max Pooling layers, a flattened layer and ten dense layers which are core components of the CNN. The platform has a multiple-stage process of input data, placement of rectangular coordinates to curve them back and the recognition of imprecise features. Over-fitting adjustment is achieved through four techniques: enhancing the existing data via data augmentation, dropout, batch normalization, and pooling, which are referred to as the unseen layers of the neural network.

Under the construction of the proposed model, characteristics like the number of filters in the convolutional levels and the kernel dimensions are overwhelming. The processed input image has shape (128*128*3) which is being filtered with 20 filters of size (5*5) in the convolution layers This setup is followed by subsequent convolutional layers with the same parameters but with smaller kernel sizes (2*2). Additionally, convolutional layers have padding and stride as key role weight and feature visualization. Thereafter, subsequent convolution operations occur, afterward Max pooling layers, and a last tier with the employing of the RELU activation function. We have the layer values as (1024, 512, 256, 128, and 64 sequentially for Tier 1, Tier 2, Tier 3, Tier 4, and Tier 5, correspondingly). Specifically, the SoftMax function performs as the output layer's activation function, which has 14,547,134 parameters. This type of architectural detail is illustrated in Figure 1 as well and thanks to this we see how the model works.

The convolutional layer is the one that does the main part of the work within a CNN as the principal layer of the network. The architecture contains fundamental modules, such as the filter for data processing and feature map, which form the so-called 'CNN core.' It has a huge impact on

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discovering a photo's main features like edge and colour. Through conducting very complex operations, the operation of the convolutional layer allows the neural network to recall the meaningful patterns of the input data, which later facilitates the analysis and classification tasks it.

Among the pooling, Maxpooling has this kind of characteristic, in which it protects the neural network from overfitting by taking the non-linear operation of the variety property. They are taught to robustly identify common details of the images however they can be scattered in different areas, shapes and colours. Hence, this procedure enables the network to learn how to correctly see the same attribute despite the representation of the image being changed. Despite that, such capabilities do not operate without performing feature mapping first, where the features that are considered important are extracted into a structured representation. Max pooling provides robustness and generalisability in neural networks to stir and achieve exceptional results in image-related tasks such as the analysis of images and classification of the same.

- ***Convolutional Layer***: The convolutional layer is a key element of CNN which is a well-known method for solving computer visualization tasks like face recognition and detection, image classifications, and predicting visual trends. It uses filters here to process data and the outputs received are called feature maps. The fact that is decisive for this layer, however, is that within it, a feature detector (enviously, "CNN core") is very important because it detects and gets features from images like lines and colours.

- ***Pooling Layer***: In its particular instance, the Pooling layer is related to geometrical variation. Regardless of any discrepancies that may be present among the images corresponding to the same entities (for instance, their presentation style, dimensions, and textures), Maxpooling provides the network with a way of finding common features beneath all these differences. This process happens before the feature map is ready.

- ***Flattening Layer***: Suppose you see the feature maps as a set of tiles. The flattening layer operates on those tiles and joins them into a long chain. As the name implies, this process plunges the multifaceted data from the feature map into a single-dimensional vector. Next, this vector ought to serve as the input for the final layers of the neural network.

- ***Max Pooling***: Max pooling which is of great importance helps in the selection of the main features of the image. It accomplishes this through an operation that identifies the highest value within a specific area of the feature maps. The fact that only the most relevant features are kept and the others are discarded by the neural network ensures its ability to function effectively.

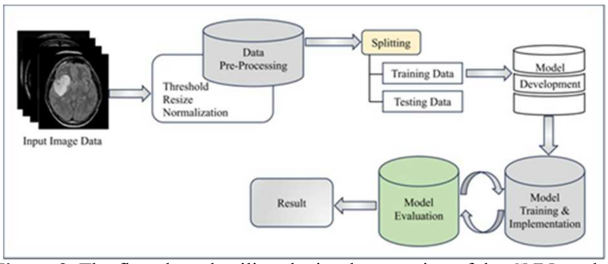

Figure 3. The flowchart detailing the implementation of the CNN model.

IV. Performance Evaluation Metrics

The performance of machine learning systems is assessed using several standard metrics, including accuracy, F1 score, recall, AUC, confusion matrix, precision, and the Receiver Operating Characteristic curve (ROC). Hence, a lot many system metrics are utilized. The indicators offer their purposefulness because they evaluate various aspects of the model's performance, which then give insight into its prediction potential.

- ***Confusion Matrix***: A confusion matrix takes place on a two-dimensional table, which is convenient for comparing the results of correct and wrong predictions of any machine learning algorithm. In terms of that, the constructed table will show where the flat of a specific model is or if the need for changes in the algorithm's design exists to increase the level of accuracy in performance. In a confusion matrix, the outcomes are divided into four primary categories: "false positives" (FP), "false negatives" (FN), "true positives" (TP), and "true negatives" (TN). These four components of the confusion matrix are illustrated in Table II.

TABLE II. Components Of The Confusion Matrix

Element	Description
TP	Images with a tumor that are correctly identified.
NP	Images without a tumor that are correctly identified.
FP	Images incorrectly classified by the CNN as having a tumor when they do not.
FN	Images incorrectly classified by the CNN as not having a tumor when they do.

- ***Loss Function***: The loss function measures the disparity between the network's predicted values and the patch of the original observations utilized for learning. The efficiency of the neural network will be the more accurate the outputs will be the desired results. It is done by an algorithm presenting the neural net in a different order by varying the neural net's weight parameters until we obtain the minimum variance between the predicted outcome and the ground truth which is known as minimization.

V. Results And Discussion

Commonly used performance metrics are typically presented to evaluate the system. These metrics include Accuracy, Recall, F1 Score, Receiver Operating

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Characteristic (ROC) curve, Precision, Confusion Matrix, and Area Under the Curve (AUC).

A. Training Results

The model undergoes training with the help of a MacBook Air with M1 chip on which Jupyter notebook environment is loaded. It enables us to gain advantage of such excellent Python libraries as TensorFlow and Keras, for example. M1 chip generated the MacBook Air with performance and efficiency including, tackling complex machine learning tasks, doing the job with no-delay. Moreover, the Jupyter notebook environment is built around a user-friend interface for source code integration and exploration. The training process gains an advantage from the MacBook Air using the new M1 chip hardware that also has the features of a GPU and thus acceleration of the computations. Now we can use the graphics processing which is equivalent to NVIDIA T4 GPU with 12 GB of GDDR5 VRAM, in the MacBook Air M1, with the highest performance quality. This hardware configuration amplifies performances as well as training duration, and it becomes very efficient when there is a need to deal with large network models for example the proposed CNN architecture. In addition, laptop has the modern processor with multiple cores and 16 GB of RAM which permits the machine to work with multiple applications simultaneously without getting bogged down. In course of training and reasoning phase, the accuracy as well as loss curves are observed and graphed to examine the model's productivity and convergence using plots generated in the Jupyter notebook working area.
Figure 5 and 6 reveal more specific information about errors and losses all through training and testing phases as well. Fig. 5 shows that there is discrepancy during the training and the testing phases, which are represented by two separate curves that are different from each other. Firstly, it is imperative to highlight that the validation accuracy always yield lower results than training accuracy, therefore, highlighting the fact that the model is a very good learner, however, the might struggle to generalize the data better when validation data is considered. In addition to this, we see that the gap occurs between the training and validation losses which are shown by Figure 6. Whenever the model achieves this, the validation loss will consistently be below the training loss making the model to improve and show signs of no overfitting in the training.

The observation that training metrics surpass validation metrics, characterized by higher training accuracy and loss compared to lower validation accuracy and loss, typically indicates satisfactory overall model performance. The above results indicate that the model is capable of doing even better once it is used to work with data and when its performance is evaluated on any unseen validation data, this is believed to have curbed the overfitting problem. The insights given in these graphs are meant to show how the CNN model has learnt, it flexibility to new data points and its generalization capability all at once.

B. Testing Results

The suggested methodology's performance was comprehensively evaluated, utilizing precision, specificity, accuracy, and ROC curve analysis, particularly emphasizing the differentiation between normal brain class and abnormal brain class. These metrics were plotted and compared to those of other classifiers to evaluate the model's performance. Specific mathematical equations for these metrics are provided below to assist knowledge/ comprehension about the evaluation process.

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \quad (1)$$

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

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (3)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (4)$$

$$\text{F1 Score} = 2 * \frac{\text{Precision} * \text{Sensitivity}}{\text{Precision} + \text{Sensitivity}} \quad (5)$$

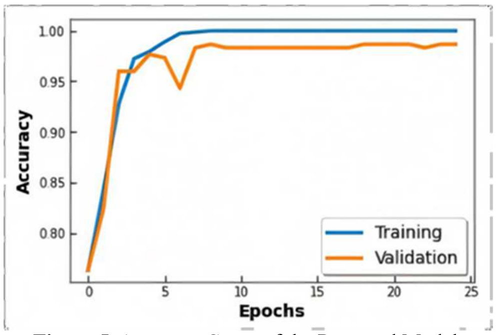

Figure 5. Accuracy Curve of the Proposed Model.

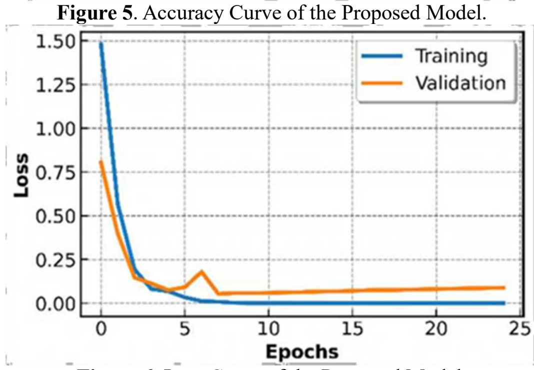

Figure 6. Loss Curve of the Proposed Model.

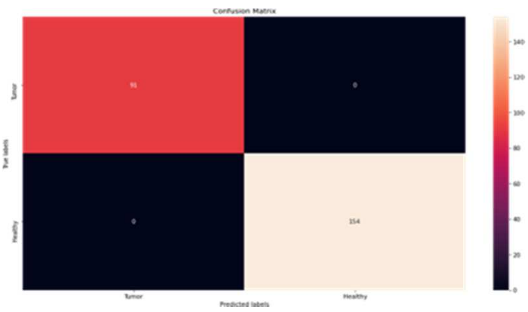
Figure 7. Confusion Matrix of the Proposed Model.

The confusion matrix of Figure 7 shows that the results extracted allow us to get to very important conclusions concerning the identification accuracy of the model. This

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algorithm was able to correctly identify 91 tumour cases and 154 healthy cases in the dataset comprising of 245 brain images. These TP and TN, as well as FP and FN, values are the ones basis is for evaluation metrics computation, like accuracy, precision and sensitivity, as shown in Table II.

Moreover, ROC has the capability to highlight the sensitivity and specificity of the model in an efficient manner whenever The ROC curve is plotted by representing the true positive rate (TPR) against the false positive rate (FPR).

The closer the area beneath the ROC curve (AUC ROC) is to 1.0, the greater is the superiority of the classification ability of the algorithm. As shown on Figure 8, AUC ROC measures the strength of CNN's classification and it is 96%, therefore, it's evident that the model has strong capability towards classify images correctly into the categories it was assigned. Below – in Table III – presents complete performance indexation set, top-level information about the proposed model functioning.

C. Discussion

The result of our study underlines the highly converged output of the new CNN model in comparison with other methods including Transfer learning models, the Random Forest classifier, ANN model, and the former CNN structures. A vital point to highlight is that our model had outstanding success and came out with an impressive accuracy of 96%. The model also was the best in the F1 score with an astounding performance of 96.5%, and precision of 97.8%. The metrics presented in the table IV, serve as proof of the efficiency of our model. They have showed that we have made a great improvement from the methods that were used in the past. Contrarily, the comparative analysis of Table IV no doubt places our model at the first rank for accuracy with the other models.

Additionally, a thorough examination of the accuracy and loss curves throughout the training and validation phases would confirm that the model wasn't experiencing overfitting, as evidenced by the consistent loss value of 0.28. This indicates that the model is effectively predicting the health condition of the brain tumour. In addition, the ROC curves validate the model and make the researchers confident that the proposed CNN model can detect and classify brain tumours appropriately.

TABLE III. ASSESSMENT OF THE PROPOSED MODEL'S PERFORMANCE BASED ON SCORING METRICS

Evaluating Metrics	Performance Score
Loss	0.2686
Accuracy	95.89%
Precision	96.73%
Sensitivity	94.8%
F1–Score	95.54%
Specificity	74.84%

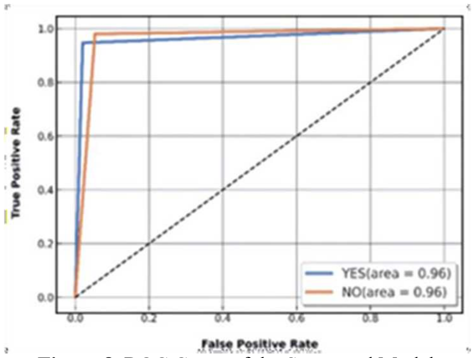

Figure 8. ROC Curve of the Suggested Model.

Moreover, an analysis of our model results was compared to the existing studies on the brain tumour detection. For example, the previous research efforts attained an accuracy range of between 82%-95.6%, applying variety of methods like support vector machine, cascaded CNN for segmentation, and Vgg19 with data augmentation. Notwithstanding the different strategies adopted by these studies, we found that our CNN model was, consistently, the champion among them, being the top- performing model in the ranking of accuracy score. Whether this model is compared to the ones those employ the similar convolutional neural networks designs or others use different segmentation methods, ours is seen to be outstanding in precise brain tumour detection and classification.

TABLE IV. COMPARATIVE SUMMARY OF SEGMENTATION ACCURACY ACROSS DIFFERENT CLASSIFIERS

Study	Method/Classifier	Accuracy Rate
[21]	CNN	92%
[24]	MobileNet V2	91%
	Inception V3	90%
	VGG19	87%
[25]	ANN	90.8%
[26]	Radom forest with ROI process	84.6%
	Radom forest without ROI process	86.7%
Proposed Study	**CNN Model**	**96%**

VI. CONCLUSION AND PERSPECTIVES

This research presents a Convolutional Neural Network (CNN) model designed specifically for segmentation of brain tumour MRI images into two distinct modules: tumour and healthy individuals we are conducting the experiments. The more profound the technique of MRI image recognition and classification went, the higher was the precision level of the neural networks which had already been utilized for comparative cases. To begin off the CNN design this medical imaging data was pre-processed with resizing in the base of the setup. The research conducted training and validation processes using a high-resolution MRI image dataset consisting of 2200 images. Regarding the performance of the CNN model, thorough evaluation was carried out using multiple metrics.

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Consequently, it can be concluded that the model outperforms other CNN models in key performance criteria, achieving an accuracy of 96% with a particularly notable accuracy rate of 98%.

On the other hand, this study underlines the capabilities of CNNs with regard to tumour fate, with CNN being the most suitable for the current data set. The study uses the performance measures of the CNN network for curve analysis, revealing the increase in the accuracy rate utilizing CNN for the classification and finding of the brain tumours over the conventional method. Other than, the article creates the concept of building of CNN and depicts these networks functioning when used on a specially created brain images database. Follow-up work might comprise of a particular plan of the proposed model and an examination of how well it works and how solid it is with a large and diverse data set, so that it can be accepted in real world applications.

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