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COMPARATIVE STUDY OF OPTIMIZATION ALGORITHMS IN CNNS FOR BRAIN MRI IMAGE CLASSIFICATION

BILAL A.OZTURK *, HAYDER MOHAMMED QASIM †, ROA'A MOHAMMED QASEM ‡, AND FATEMEH KHAMOUSHI §

Abstract. Brain MRI often reveals long-standing diseases of the nervous system, such as multiple sclerosis, dementia, a stroke, and brain malignancies. In addition to that, the most accurate method of brain MRI, besides the diagnosis of pituitary gland diseases, is the method diagnosing the vessels of the brain and eyes and the organs of the inner ear. On the other hand, many methods of loading medical pictures have been developed with brain MRI data, often to diagnose diseases and monitor health via it. Convolutional neural networks belong to deep learning and are widely used for input from the visual domain. The most common use of CNN is in natural language processing and recommendation systems, image classification, medical imaging, and image and video recognition. This work is divided into several parts. The Msoud dataset, used in this study, consists of 7023 MRI images, which were made by the Fighshare, SARTAJ, and Br35H datasets. The MRI images are of four classes, that is, healthy brains, brains with glioma, brains with meningioma, and pituitary. In this research work, the doing of different pre-processing of the MRI input to make the images ready for the model to be trained is done. The architecture is made up of dense layers such that after each set of convolutional layers, there is a max-pooling. Eventually, batch normalization and dropouts in the training are stabilized to reduce overfitting. The proposed CNN compared with other studies and many transfer learning models found the proposed model to achieve significant accuracy of 99.00%, 98% and 97% for using Adamax, Adam and RMSprop optimizers respectively.

Key words: Convolutional Neural Network, Classification, Brain Tumour, Optimization, Deep Learning.

1. Introduction.

A brain tumour, frequently referred to as BT, is a malignant expansion of brain cells that appears as a growing mass or tumour. It is made up of a component that is aberrant and not like the other cells. While tumours with cancer are consist of living, cancerous cells have a unique structure, benign brain tumours are composed of non-living cells. The two types of these malignancies are categorized as primary and recurrent. Whereas cancers that have metastatic properties spread to other parts of the body, primary tumours occur inside the brain. Brain tumours can occur in children and adults and are one of the most fatal diseases in the world. They are the third most common cancer in teenagers and young adults and the most common in older adults. For example, meningioma, pituitary, and glioma. Gliomas, which occur in the spinal cord and parts of the brain, which includes the cerebral pedicle, cause symptoms like pain, headaches, and vomiting. They are responsible for 80% of the malignant brain tumors that occur in the primary level. Lymphoma is a form of brain tumor whose incidence is rapidly increasing, resulting in an extremely high fatality rate. Meningiomas develop in their meninges which are the membrane tissues located in the areas of the brain and the spinal canal. Pituitary tumours are caused by the pituitary gland's aberrant growth. These tumours are usually not malignant [1].

Diagnosis of brain tumours Diagnostic procedures of brain tumours can be made through physical and neurological examinations besides CT and MRI. As MRI is non-invasive and non-ionizing, it is opted for rather than CT. General confirmation of its diagnoses is generally done by pathological investigation and a biopsy. A treatment plan is developed when the kind and stage of cancer have been determined. Due to the enormous number of patients, human evaluation of medical photos is complicated and error prone. Early brain tumour detection studies call for much more advanced work. The images through MRI are often exposed to noise, which needs to be removed appropriately [2]. Brain tumours bear tentacles and fluorescent characteristics, making

*Faculty of Engineering, Istanbul Aydin University, Istanbul, Turkey.(bilalabed1978@gmail.com)
†Faculty of Engineering, Istanbul Aydin University, Istanbul, Turkey.
‡Faculty of Engineering, Istanbul Aydin University, Istanbul, Turkey.
§Faculty of Engineering, Istanbul Aydin University, Istanbul, Turkey.

their separation a clumsy task. Very critical is the choosing of the best features and their extraction, and therefore determining the sample size appropriate for classification. Feature learning has been an automatic process for many and is much appreciable, although it demands huge computational resources and memory. Lately, henceforth, lightweight models have been developed that give high accuracy with minimal computation. There are recent models that address the whole of the tumour, although not focusing on some regions effectively.

To address these issues, the authors propose constructing an autonomous computer-aided diagnostic system. An automatic computer-aided diagnosis system would simplify the categorization and diagnosing process of brain MRI images for radiologists and doctors.

The key contributions of our study are the followings. We introduced a newly fine-tuned pre-trained model, EfficientNetB3, Classifying the four forms of tumours: glioma, meningioma, pituitary, we compared that approach with multiple sophisticated designs and evaluated its efficacy. We employed convolutional neural networks (CNNs), which can extract intricate patterns and fine detail in MRI data for improved diagnostic precision. The approach, based on large datasets and cutting-edge neural network architecture, is considerably better than previous approaches, reducing the number of false positives and the danger of misdiagnosis.

This research describes a thorough examination into the categorization for brain tumour MRI images utilizing DL's. The study's significant contributions are outlined below:

- Data Augmentation and Preprocessing: These strategies are vital for generalizing the model. To do this, the ImageDataGenerator function was used to preprocess pictures with a modification in the set of batch processing settings and sizes, allowing for more effective training and validation. The technique contributed to the development of a highly powerful model through extensive exposure to numerous picture alterations.
- Model Architecture and Training: The model architecture of the study was closely like the state-of-the-art CNN, EfficientNetB3, well known to its efficiency with performance. To prevent overfitting, fine-tuning was done by adding batch normalization, dense layers with regularization, and dropout layers.
- Advanced Techniques Implementation: The abovementioned advanced machine learning techniques include regularization methods, which are responsible for avoiding data overfitting and attuning the model for generalization. The hyperparameter tuning and the model optimization approach are advanced for deep learning models about training for medical image classification.
- Repeatability and practical application: This would describe a repeatable paradigm of the classification of MRI images, which will be very useful to both medical users and researchers. Implementation details with necessary steps and code will ensure the derived methodology can be easily adapted and further expanded for other similar tasks of medical image analysis. This will further foster ongoing research and development in this area of medical image analysis.

In general, this work demonstrates the application of deep learning techniques in an effective way to contribute to the challenging problem of brain tumor classification, which remains an important area in medical imaging and diagnostics.

2. Related work. Gwak et al. [3] presented a model based on deep feature and ML classifiers compared to ensemble learning models. The researchers collected information from brain MRI scans applying a deep convolutional neural network (also known as CNN) and transfer learning techniques. Various ML classifiers were then utilized to assess the retrieved deep features. A feature collection is created by combining the top three deep learning, which demonstrate strong performance in the machine learning classifier. The model's success can be considerably enhanced by the ensemble performance derived from deep features, as demonstrated by the experimental data.

Chenjie Ge et al. [4] a graph-based semi-supervised learning model for IDH mutation prediction and glioma classification is presented. Test accuracy for the model was reported at 86% on the TCGA data and 90% on the MICCAI data, based on testing it on two glioma datasets.

Das et al. [5] investigated brain tumour disorders using the CNN architecture. Their main goal has been to develop a CNN model that can identify brain tumours using T1-weighted, contrast-enhanced MRI scans. The proposed approach is divided into two basic stages: CNN is used for classification after images undergo pre-processing applying a range of methods for image processing. Pituitary adenoma, meningioma, and glioma are the three forms of brain tumours shown in the study set of 3,064 images. The test accuracy was 94% when they used the CNN model. Moreover, genetic algorithm and support vector machine were utilized by Narayana et al. [6] to categorize and segment brain MRI data. The accuracy rate of categorizing brain MRI scans either normal or abnormal was around 91%.

Kumar et al. [7] proposed approaches for a separate experiment. Three categories of machines are interconnected: support vector machine (SVM algorithm), artificial neural networks (ANN), and suggested technique involves preparation, the process of segmentation feature extraction, and classification.

First, the median filtering technique is utilized to an input MRI image to perform pre-processing procedures. Next, the FCM clustering technique is used to carry out segmentation. In the third step, the Grey Level Co-occurrence Matrix (GLCM) is applied to extract features. Ensemble classification is used to establish the automated stage of a brain tumour. The ensemble classifier is used to discriminate between photos with and without tumours. The procedure was found to be more exact, efficient, and dependable because of the experiments. The proposed approach achieved an accuracy of 91%.

Jibon et al. [8] recommended a classification system that employs CNN and log-polar transform (LPT) to distinguish between malignant and non-cancerous tumours in MRIs. While CNN integration introduced a machine learning method for classifying tumours from damaged images, LPT was utilized to retrieve rotation and scaling information from damaged photos. Because of rotation and scale invariance, the ML approach was found to be more successful in classifying individual MRI images as well as brain MRI images.

Sultan et al. [9] created a CNN-based DL system to identify three kinds of brain tumors from two publicly available datasets.

Yazdan et al. [10] proposes a multi-class classification technique for using magnetic resonance imaging (MRI) to identify instances of Glioma, Meningioma, Pituitary, and No Tract. In terms of precision and effectiveness, the results of experiments showed that the proposed multi-scale CNN model outperformed AlexNet and ResNet while requiring fewer computational resources. The approach has a 91% F1 score and an accuracy rate of 91%.

A. Asiri et al. [11] suggested a method for reducing the parameter-heavy character of CNNs by utilizing involutional neural networks (InvNets) for brain tumour classification. The InvNet architecture attained a 92% accuracy rate.

There have been other methods proposed for classifying brain tumours, which suffer from several deficits of their own. For example, none of the available approaches are good enough to classify brain tumours, which is critical in the medical field. With most of the procedures, reliance on manually outlined locations of the tumours does not support full automation. Previous efforts based on such techniques using the Convolutional Neural Networks (CNN) and their variants do not bring any significant performance improvement. Hence, other metrics than accuracy need to be referred to while evaluating the performance. Moreover, models based on CNNs perform very badly when implemented with small datasets such as medical image databases.

3. Methodology. We offer the architecture for categorizing brain tumours utilizing to three-layer CNN, with the core framework based on the EfficientNetB3. The EfficientNet models stand out for their remarkable effectiveness and speed in a wide range of machine vision algorithms, particularly medical image processing. Figure 1 depicts the flowchart for the CNN model. Figure 3.1.

3.1. Dataset Description. The collection of data was utilized for training, validation, and testing. This open due dataset includes 7023 grayscale MRIs in JPG format with different human brain types. The developed models were analysed and validated using this dataset with different CNNs. The collection of data was acquired using three distinct sources: figshare, the SARTAJ dataset, and Br35H. The dataset has four classes of brain tumours: Glioma (training images: 1321, testing images: 300), Meningioma (training images: 1339, testing images: 306), No-tumour (training images: 1595, testing images: 405), and Pituitary (training images: 1457, testing images: 300).

3.2. Data Pre-Processing. Data preparation refers to preprocessing of data in which data is cleaned, prepared, and fine-tuned. This makes the model better in its prediction. The challenge is mostly presented by MRI datasets in the sense that the brain images of the subjects are of different sizes, whereby the width, height, and overall size may differ. All images have been made into one single dimension for training.

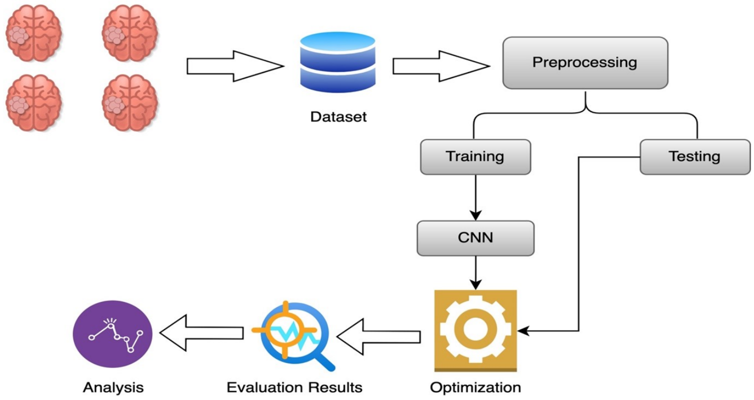

Fig. 3.1: The CNN Model Flow Chart.

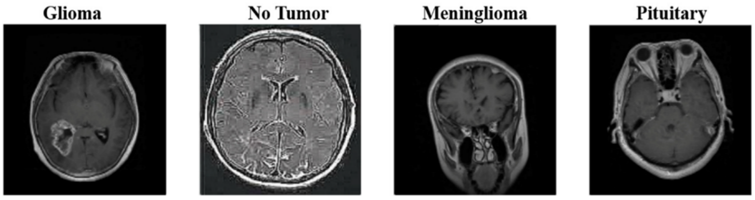

Fig. 3.2: Sample Images for Brain Tumour Dataset.

3.2.1. Data augmentation. The augmenting data is an interesting method to increase the efficiency and generalization of DNNs under normal conditions when labelled data is scarce. Data augmentation provides an excellent strategy for training DL models on seismic data because they are model-agnostic techniques and have low computational cost compared to the training process. One of such regularization techniques is data augmentation, which enhances the invariance of the dataset, injecting more invariant examples through label-preserving modifications. It is empirically demonstrated to be effective in reducing overfitting during training of CNNs for classification tasks. Data augmentation has an essential way to overcome problems like uneven distribution and data shortages. It has been implemented in several studies for brain tumour classification involving geometric transform operations like changes in brightness, zoom, or scaling and rotation. For example, common data augmentation methods are random cropping, flipping, and color adjustment techniques [12]. Together with Taylor, DeVries [13] presented Cutout, which generates enhanced pictures by systematically slicing out cube areas of input photos. Drop out also loses undetected nodes from a network at random throughout the training phase [14]. Popular methods that drop random hidden nodes in networks include Maxout [15], Continuous Drop out [16], Drop Path [17], with the stochastic depth [18], the last of which is based on the method to produce. For example, during training, stochastic depth randomly loses part of the remainder branches in a ResNet, causing the network size to decrease. Dropout now has many variant forms, and a new one is Drop Block [19], in a feature map, the nearby areas. Drops nearby regions on a feature map. Weight decay, or Tikhonov regularization, supplements a norm penalty of weight at a parameter to the loss function widely in neural networks and in linear inverse problems [20]. For example, DisturbLabel [21] augments the data by introducing noisy labels but in return suffers in performance. Recently, shake-shake-based regularization has been proposed to mix features within CNNs and obtain cutting-edge classification performance [22], [23].

3.2.2. Regularization. Regularization is a technique to prevent overfitting by changing the procedure of the model's training and its architecture. The most common regularization techniques are: L2 regularization, L1 regularization, Dropout Regularization.

The L2 regularization of regression analysis is commonly referred to as ridge regression. The technique is such that it adds the squared coefficients/weights norm, multiplied by some kind of regularizer term, to the loss or cost function.

L1 regularization is popularly referred to as lasso regression, where the absolute value of the magnitude of the coefficients or weights is added to the loss or cost function alongside a regularizer.

Previous research has demonstrated that regularization enhances categorisation performance in deep models. The implementation first employed the notion to enhance the efficiency of the conception model when processing ImageNet data. The fact remains that several released models for image classification have welcomed regularization up to this time. Although very popular since it has many characteristics such as a classification boost and speeding up the convergence method, its incorporation in HSIC is not investigated. Also, when and why it should be effective is not well understood.

3.3. Convolutional Neural Networks (CNN) Architecture. In this study uses a dataset of MRI brain scans that already has data categorized with either having a tumour or not. The data is easily separated into two primary groupings, i.e., training as well as testing. The dataset is gathered by iterating over directories of the respective categories, pulling file-paths and labels compiled into Pandas data-frames for both training and testing. CNN was used to classify patients with or without tumour in the dataset used. To begin, in pre-processing, ImageDataGenerator was utilized to handle the photos during model training, allowing the data to be processed efficiently through proper batch processing.

The CNN [24] architecture is the most common type of ANNs in practice today, and it is widely implemented in pattern recognition applications using images. Object identification, then, becomes the process of picking out some distinctive patterns from the input, which are recognized through a layer of deep, hidden layers. The first few layers of the network recognize easy patterns, such as lines and curves, and the more layers added, the more complex the patterns recognized can become, such as faces. These networks have been formed with a focus on image processing and have been motivated by the operation of the visual cortex in image processing and recognition. Convolution mainly focuses on the detection and learning of characteristic patterns that will help in the determination and categorization of objects based on their knowledge of features include curves, lines, as well as colour tones. The input/output layer, convolution layer, pooling layer, nonlinearity or function of activation layer (ReLU), and final classification layer make up the standard CNN design.

CNN have been applied largely to most applications that rely on artificial vision techniques [25]. While showing a lot of promise in such application domains, CNNs bring high computational costs, hence the need for techniques that exploit and optimize the computation cost without affecting the performance. Thus, the present paper introduces the capability of tuning CNN parameters in order to reduce computational costs and further augment recognition rates.

The CNN model architecture included a convolutional neural network. Table 3.1 demonstrates the CNN model structure. The basic model then adds a few more layers:

1. The batch normalization method is used for normalizing previous layers activations and stabilise the process of learning.
2. It has a 256-unit dense layer appended to it, where both L1 and L2 regularization are added to avoid overfitting by imposing a penalty for large weights.
3. Dropout layer in which the dropout rate is 0.4 and the units are dropped randomly during training to avoid the co-adaptation of neurons.
4. The output layer is of the dense type with a softmax activation to assign probabilities to classes.
5. It was built utilizing the Adamax optimizer, which has a rate of learning of 0.001. The loss function that was utilized was classified cross-entropy; This type of reduction function is frequently employed in multi-class occupation categorization.
6. The approach used is trained utilizing the training set of 10 sessions, and then validated using a previously produced validation dataset. Model efficiency measures, like accuracy and loss, ability to be checked regarding to both the sets of training and validation used in the learning technique and updated as needed.
7. The model is validated after training against the training, validation, and test data to check the achieved

Table 3.1: The parameters for the suggested CNN model are given below.

Parameter	Value
Input Shape	(224, 244, 3)
Pooling	Max
Batch Normalization	Momentum: 0.95, Epsilon: 0.01
First Dense Layer	Units: 256, Activation: ReLU, Regularizers: L2(0.016), L1(0.006)
Dropout	Rate: 0.4, Seed: 75
Second Dense Layer	Units: classes number, Activation: Softmax
Optimizer	Adamax, Learning Rate (lr): 0.001
Loss Function	Categorical_Crossentropy
Metrics	Accuracy
Epochs	10
Batch Size	16
Image Size	(224, 244)

generalization capabilities. Performance is measured using accuracy and loss metrics.

Visualization. Training accuracy, cross-validation, and loss plot are displayed to show changes in overfitting and underfitting. Confusion matrix of the test set predictions to get a broad understanding of the model's effectiveness across different classes. Validate the data processing by seeing example images from the training set.

Finally, it makes predictions on the test dataset and forms a full classification report, giving details on recall, f1-score, precision, and support of each category; therefore, giving detailed performance of the model. This is aimed to ensure that the CNN performance is evaluated exhaustively in classification competency for MRI images based on the presence of brain tumours, taking this into consideration with practical application and vigorous performance validation.

4. Result. The thorough analysis provided a key factor of assessment: the training and validation accuracy and the measure of the loss. The detailed analysis was based on behaviour of individual classes from a confusion matrix. The programming language implemented to design the proposed model is Python. With its simplicity, flexibility, and collection of libraries, Python is more popular in the field of neural networks and machine learning. The basic libraries applied for neural networks (NN) are TensorFlow (TF), Keras, and Matplotlib. TF is a Python library tool for deep learning developed by Google; a whole set of tools and functions are available to efficiently build and train neural networks. The CNN model performance with the brain tumour dataset is measured using a variety of evaluation criteria, including accuracy, recall, precision, and F1 score [26].

Accuracy explains how to calculate the efficiency of the classifier based on the expected accuracy ratio. It can be identified as stated in Equation (4.1).

$$Accuracy = \frac{TP + FN}{TP + TN + FP + FN} \tag{4.1}$$

Recall it is a statistic that represents the proportion of positive processes that need to be estimated. It can be identified as stated in Equation (4.2).

$$Recall = \frac{TP}{TP + FN} \tag{4.2}$$

On the other hand, precision indicates the percentage of estimated positive values that are actually positive. It can be identified as stated in Equation (4.3).

$$Precision = \frac{TP}{TP + FP} \tag{4.3}$$

The F1 Score is obtained through calculating the harmonic average of precision and recall; it employs a harmonic mean since extreme situations are not ignored, just as a simple average does. For example, if we had

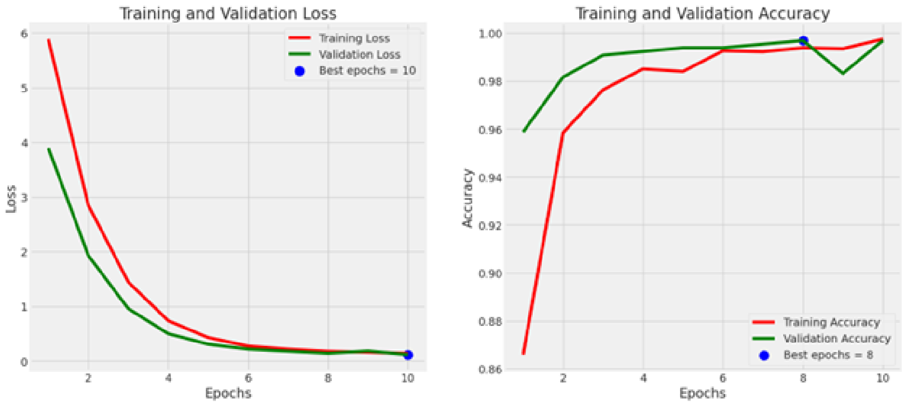

Fig. 4.1: Loss and Accuracy for training & validation.

computed using a simple average, the accuracy of a 1 and recall of 0 model would yield an F1 score of 0.5, which is extremely deceptive. F1 Score can be identified as stated in Equation (4.4).

$$F1 = \frac{2 * Precision * Recall}{Precision + Recall} \tag{4.4}$$

Figure 4.1 shows the procedure of developing and validating a classification model for this research. This graphic demonstrates that the model learned well on the initial training data and generalized well on the validation data. A quick reduction in training as well as validation losses suggests successful learning and a reduction in prediction mistakes. The relatively small gap between the training and validation lines of loss provides the appearance that the model does not overfit, however this is an overfitting instance because the accuracy of validation is high and consistent. The fact that training accuracy approaches 1.0 indicates that the model can accurately predict the training data to a great extent. In general, these graphs suggest an accurate model with strong generalization, which leads to excellent training and validation performance.

Figure 4.2 shows a confusion matrix that summarizes the DL model's performance in classifying brain tumors. The model works very precisely, which is well observed by the great diagonal presence representing a big amount of correct predictions for each class: precisely, 147 observations are right with glioma, 148 with meningioma, 208 without tumor, and 150 observations with the pituitary tumor class. There is very little confusion: precisely just 2 cases with glioma and 1 pituitary tumor were wrongly classified as meningioma. In its essence, this robustness and trust in identifying glioma, meningioma, no-tumor, and pituitary-tumor cases presents a force to be reckoned with in clinical diagnostics, thus helping medical professionals in identifying tumors accurately and promptly.

Table 4.1 shows the results using the RMSprop optimizer with CNN with brain tumor data set, where the overall accuracy reached 97% for all classes.

Table 4.2 shows the results of different evaluation metrics using the Adam optimization tool with CNN on brain tumor data set. The results showed an increase of 1% in the accuracy.

Table 4.3 shows a high result with all the evaluation metrics by using CNN with Adam optimizer where reached the accuracy, precision, recall, and F1 score to 99%.

A comparative analysis of different methods in performance metrics for different studies is shown in Table 5. Methods include Decision Tree [25], Random Forest [25], fused-based methods [26], Deep Neural Network [27], and Involution Neural Network [11]. From this table, it is evidently seen that the performance of the proposed Convolutional Neural Network was prominent with all existing methods in terms of the measures of accuracy, precision, recall, and F1-score. These depict a highly improved performance compared to the past approaches.

5. Limitation. A summary of state-of-the-art approaches to diagnosing brain cancers as meningioma, glioma, or pituitary tumors: When it comes to the key classification problem for a critical medical purpose, all

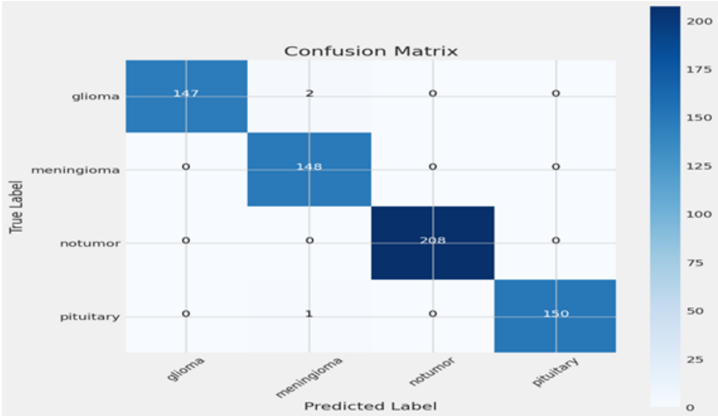

Fig. 4.2: Confusion matrix for convolution neural network.

Table 4.1: The evaluation outcomes of the proposed CNN model using the RMSprop optimizer.

	Precision	Recall	F1-score	Support
Glioma (class 0)	99%	96%	97%	151
Meningioma (class 1)	95%	95%	95%	164
Notumor (class 2)	97%	99%	99%	192
Pituitary (class 3)	99%	98%	99%	149
Accuracy			97.0%	656
macro avg	97.1%	97.2%	97.1%	656
weighted avg	97.1%	97.1%	97.2%	656

Table 4.2: The evaluation findings using the Adam optimizer for the proposed CNN model.

	Precision	Recall	F1-score	Support
Glioma (class 0)	99%	95%	97%	151
Meningioma (class 1)	98%	96%	97%	164
Notumor (class 2)	99%	99%	99%	192
Pituitary (class 3)	96%	99%	98%	149
Accuracy			98.1%	656
macro avg	98.1%	98.2%	98.1%	656
weighted avg	98.1%	98.1%	98.2%	656

cutting-edge approaches fall well short. The previous methods needed manual delineation of the tumor regions before classification and therefore never became completely automated. The automatic algorithms developed by the use of CNNs or their variants have not been able to significantly enhance the performance. Moreover, these methods were tested on an imbalanced image dataset, so evaluation through other metrics besides accuracy is needed. Finally, none of these studies related to the issue of data scarcity, which may often happen in applications. Convolutional neural networks are now a mature and standard tool for classifying images in the diagnosis of medical diseases, but developing just one single model applicable to different tasks that might be useful is in many cases neither practical nor feasible. For each problem, a different CNN model would have to be designed from scratch based on the nature of the problem, the inputs, and the expected outputs of these models.

Table 4.3: shows the evaluation results of the proposed CNN model with Adamax optimizer.

	Precision	Recall	F1-score	Support
Glioma (class 0)	99%	99%	99%	149
Meningioma (class 1)	98%	99%	99%	148
Notumor (class 2)	99%	99%	99%	208
Pituitary (class 3)	99%	99%	99%	151
Accuracy			99.0%	656
macro avg	99.1%	99.1%	99.1%	656
weighted avg	99.2%	99.1%	99.1%	656

Table 4.4: Comparative analysis with other studies

Study	Method	Accuracy	Precision	Recall	F1-score
Pandarakone et al. [27]	Decision Tree	78.75%	-	-	-
Pandarakone et al. [27]	Random Forest	80.75%	-	-	-
Amin et al [28]	Fused-based methods	Avg 86%	-	-	-
Kumar et al.[29]	Deep Neural Network	89%			
Asiri et al.[11]	Involution Neural Network	92%	92.5%	91.75%	92%
Proposed	CNN	99%	99%	99%	99%

6. Conclusion. The proposed approach is aimed at achieving the necessary optimal accuracy in the classification of images and reducing the level of error. We propose to use a custom convolutional neural network architecture to enhance the performing accuracy of the dataset. This work focuses on the use of CNNs to identify MRI images. This work tried to find out the best Deep Learning classifier for the automatic classification of tumour cases with the help of an MRI dataset. The brain tumours identified were no tumour, pituitary, meningioma, and glioma. The results from the experiments prove that the proposed model classifies brain tumours with an accuracy of 99% with the dataset disclosed earlier. It can be further validated with a wide variety of datasets. Future research studies may be based on the scale and the properties of generalization of the proposed methodology in relation to larger and more diversified datasets. Interpretability of CNN models, when researched and combined with different optimization algorithms, will help to increase the accuracy and robustness of disease detection.

Future work. Future research studies may be based on the scale and the properties of generalization of the proposed methodology in relation to larger and more diversified datasets. Interpretability of CNN models, when researched and combined with different optimization algorithms, will help to increase the accuracy and robustness of disease detection.

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