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Enhancing Multi-Class Tumour Detection with DenseNet121: A Deep Learning Approach in Medical Images

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ABSTRACT

Technology has played a pivotal role in revolutionizing healthcare through digital transformation. Healthcare systems now include a vast infrastructure of medical information systems, electronic devices, medical records, wearable and smart devices and mobile devices. The progress in medical infrastructure, coupled with advances in computational methods, has enabled the researchers and practitioners to develop new solutions. The present work intends to articulate the essentiality of enacting CNN deep learning with Transfer Learning technology for efficient brain tumour detection and classification. In the proposed work, a strong data set including 2,870 training images and 394 test images considered with four class detection; MRI scans respectively tumour classification data and site segmentation of the tumour and some augmentation data are used to enable model implementation to improve training as well as testing. Fine training the deep learning model, where dense neural architecture (DenseNet-121) is trained using pre-processed MRI images. The obtained training and validation accuracies are 99.98% and 98.72%, respectively. Evaluation metrics, including precision, recall and F1 score, confirm the exceptional performance of the model in identifying and classifying brain tumours. Visualizations such as confusion matrices, training/validation loss and accuracy plots provide comprehensive insights into the typical training process and its overall effectiveness. These results demonstrate the potential of the proposed approach to significantly advance the diagnosis of brain tumours, ultimately benefiting patients.

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1. Introduction

Through digital transformation, technology has been instrumental in transforming healthcare. Healthcare systems now encompass a broad infrastructure of medical information systems, electronic devices, medical records, wearable and smart devices and handheld devices. The development of novel solutions has been made possible by the expansion of the medical infrastructure and the progress made in computational methods. One study aimed to identify the key factors influencing individuals' adoption of wearable devices in healthcare. Recent research by Yang *et al.,* [1] and Asadi *et al.,* [2] provides a comprehensive overview of the existing literature on the Industrial Internet of Things in healthcare.

Another systematic literature review focused on the use of mobile computing in healthcare was conducted by Nazir *et al.*, [3]. Between 2015 and 2019, the fields of big data management in healthcare systems, analytics and scientific programming witnessed a remarkable revolution. Much research and articles have been published that have explored this field and revealed the great progress that has been achieved in it, as discussed by Nazir *et al.,* [4]. Patient data and information are now consistently stored to ensure easy access and retrieval. Traditional healthcare has been digitalized by Internet of Things (IoT)-based applications like wearable technology, mobile phone healthcare systems and electronic medical record generators. These advancements enable physicians to remotely monitor and treat patients, even in remote areas. Mobile health (M-health) procedures provide a platform for delivering essential clinical services and present numerous opportunities for highly skilled specialists, as illustrated by Xu *et al.*, [5] and Wu *et al.*, [6].

M-health procedures utilize technologies like Tactile Internet, 5G and AI to solve asset booking issues. An innovative study explored remote healthcare based on 5G Tactile Internet and AI, introducing a fog-assisted intelligent model to reduce remote healthcare inactivity, as shown by Tiwari *et al.*, [7]. Activity detection and classification using diverse sensor modalities have become pioneering technologies for behaviour analysis, daily activities of real-time monitoring, rehabilitation, ambient assisted living, smart home surveillance, elderly care and entertainment.

Smartphones, wearable devices and ambient environment devices, including a magnetometer, heart rate monitor, accelerometer, pressure sensor and wearable camera, integrated. Different sorts of smart sensors are defined to identify activities and monitor persons' activities, as demonstrated by Strudwick *et al.*, [8] and Nweke *et al.*, [9]. Algorithms are used to extract features from pre-processed sensor data through learning methods. For instance, frequency domain, time domain and wavelet transform are machine learning algorithms used for human activity monitoring and classification. Deep learning techniques are developed to enhance performance and automatically feature extraction, eliminating the need for handcrafted feature-specific algorithms.

In the modern era of healthcare, artificial intelligence techniques such as deep learning and data science play a crucial role in early detection, analysis, management and presentation. Smart devices such as advanced equipment, IoT devices, robots, drones and webcams have proven useful, particularly in pandemic situations, as indicated by Sufian *et al.*, [10]. Transfer learning is a machine learning technique where a model developed for a particular task and then reused for another model on a second task as starting point. It is considered as a form of domain adaptation, offers a new solution to mapping feature and label structure distribution, according to Gardner *et al.*, [11] and Zhang *et al.,* [12]. However, there is a need for a comprehensive report on the current literature regarding deep learning and transfer learning in modern healthcare. To address this gap, the proposed study aims to build a proactive deep learning approach for health data (such as image cancer diseases) using of transfer learning and an advance technique of DenseNet-121.

This paper is organized as follows: Section (2) discusses the related work in detail and deep learning approaches. Section (3) explains the details of the proposed methodology. In Section (4), we discuss the results and empirical analysis in terms of metrics, performance and comparison against multiple state of the art approaches. Finally, we conclude our work and discuss its future directions in Section (5).

2. Related Works

In this section, previous works related to the study are presented, where important techniques are highlighted and the strengths and determinants of the studies are identified for deep transfer learning in the sector of healthcare monitoring data.

The study "Brain Tumour Classification Using Convolutional Neural Network", by Nyoman Abiwinanda *et al.,* [25] was extended and discussed by Raza *et al.,* [13], who employed deep neural networks with transfer learning, specifically using a pre-trained InceptionV3 model, to classify brain tumours from MR images. The dataset consisted of 3,064 T1-weighted MR images from 233 patient cases with meningioma, glioma and pituitary tumours. Three image-level models and one patient-level model were built and evaluated using metrics such as accuracy, loss, precision, recall, kappa and AUC. The models were validated using various approaches, including holdout validation and cross-validation. The patient- level model achieved the best accuracy of 99.82% in group 10-fold cross-validation.

The work of Hidayatullah *et al.,* [28] aimed was further analysed by Chen *et al.,* [14], who aimed to develop a CNN classifier to automatically recognize normal chest radiographs and those with pneumonia, addressing the limitations of manual diagnosis and time-consuming processes. They utilized various architectures: VGG16, VGG19, InceptionV3, Xception DenseNet121 and ResNet50. Although the researchers achieve good results using VGG16, with training accuracy of 98.24% and validation accuracy of 92.15%. Finally, they concluded that VGG16 was the best option among the tested architectures.

The study " Brain MRI-based Wilson disease tissue classification: an optimised deep transfer learning approach" by Saba *et al.,* [26] was enhanced and examined by Dawud *et al.,* [15], introduces an optimised deep transfer learning approach for classifying Wilson disease (WD) using brain MRI images. The method leverages MobileNet and Visual Geometric Group-19 (VGG- 19) transfer learning paradigms and an ensemble of convolutional neural networks (CNNs). CNNs are fine-tuned on a large dataset of natural images to extract high- quality features for WD classification. The transfer learning models are compared with K-nearest neighbour, Decision Tree and Random Forest ML models. Data augmentation techniques address class imbalance. The dataset comprises T2- weighted Turbo Spin Echo MRI scans from 46 patients. MobileNet achieves an accuracy of 86.87% and an AUC of 0.868, while VGG-19 achieves 95.46% accuracy and 0.954 AUC. The transfer learning models outperform ML models, with 3.4% and 13.5% improvements over Random Forest.

The proposed approach "Designing ECG Monitoring Healthcare System with Federated Transfer Learning and Explainable AI" was discussed by Pathak *et al.*, [16], is an end-to-end framework for ECG-based healthcare that combines explainable artificial intelligence (XAI) and deep convolutional neural networks (CNNs) in a federated setting. The framework utilizes a CNN-based autoencoder to denoise raw ECG signals and a CNN-based classifier to effectively classify different arrhythmias. An XAI-based module is incorporated for interpretability of the classification results, aiding clinical practitioners in making reliable decisions. The framework achieves high accuracy, with the trained classifier achieving up to 94.5% and 98.9% accuracy for arrhythmia detection using noisy and clean data, respectively, in five-fold cross- validation. This approach offers improved performance, privacy preservation, interpretability and can be applied to various healthcare applications.

The paper "FedHealth: A Federated Transfer Learning Framework for Wearable Healthcare" by Chen *et al.,* [27] was expanded upon by Szeliski [17], introduces FedHealth, a federated transfer learning framework designed for wearable healthcare applications. The method combines federated learning and transfer learning techniques to overcome the challenges of privacy-preserving data aggregation and personalized model building. For human activity recognition, a convolutional neural network (CNN) architecture is utilized. The researchers employ the UCI Smartphone dataset, which comprises data from 30 users and encompasses six activities. The experimental results demonstrate the effectiveness of FedHealth, as it achieves higher accuracy compared to the traditional method (NoFed). Specifically, for subjects P1, P2, P3, P4 and P5, FedHealth achieves accuracies of 98.8%, 98.8%, 100.0%, 99.4% and 100.0%, respectively, while NoFed achieves accuracies of 94.5%, 94.5%, 93.4%, 95.5% and 92.6%. The overall average accuracy improvement of FedHealth over traditional methods is reported as 5.3% for wearable activity recognition. Deep learning approaches have also shown promise outside the healthcare sector, as illustrated by Marza *et al.*, [18].

Dawud *et al.,* [15] work on identifying brain haemorrhage in early stages using deep learning and transfer learning concepts was further investigated by Jiang [19], the authors address the challenging task of identifying brain haemorrhage in early stages using a deep learning approach. They propose two models: a modified version of the AlexNet neural network with an SVM classifier (AlexNet-SVM) and a CNN created from scratch. The objective is to investigate if fine-tuning a pretrained model through transfer learning can eliminate the need to build a CNN from scratch. The models are trained on a dataset of brain CT images and evaluated on 30% of the available data. The results show that AlexNet-SVM achieves the highest accuracy of 93.48%, outperforming both the CNN (90.65%) and the original AlexNet (92.13%) in identifying brain haemorrhage. AlexNet-SVM also exhibits a lower mean square error (MSE) of 0.054 compared to the original AlexNet (0.087) and the CNN (0.092). The learning curves indicate that training the deeper models requires longer time and more epochs. Visualizing the learned features in the convolutional layers provides insights into the different levels of features learned.

Pathak *et al.*, [16] development of a classification model for COVID-19 patients using deep transfer learning was built upon and compared by Buduma *et al.,* [20], is to develop a classification model for COVID-19 infected patients using deep transfer learning. The authors address the challenge of classifying COVID-19 patients from chest CT images, incorporating deep transfer learning and a top-2 smooth loss function with cost- sensitive attributes. The proposed model is compared to other supervised learning models using a dataset comprising 413 COVID-19 positive images and 439 images of normal or pneumonia-infected patients. The results show that the proposed deep transfer learning-based model achieves significantly higher accuracy, precision, sensitivity, specificity and overall performance compared to existing models. The training and validation analyses demonstrate the effectiveness of the proposed model, with training accuracy reaching 96.2264% and validation accuracy achieving 93.0189%. These findings indicate that the proposed model is a viable alternative to COVID-19 testing kits. Future work could involve further optimization of hyperparameters and the use of lighter deep learning architectures to improve the performance of the model. Besides, deep learning has a broader applicability, not just in the health care application of the field.

Research on DL and ML-based MRI approaches for brain tumour detection presented by Anantharajan *et al.,* [21] was validated. The initial approach of using a median filter and an adaptive contrast enhancement algorithm is put to collect and pre-process the MRI configuration. The segmentation is performed by the fuzzy approach segmentation process trimming the pre-process configuration. The Gray Level Co-occurrence Matrix (GLCM) of is used for a selection of the features extraction. The Deep Neural Support Machine (EDN-SVM) classifier applies to classify the aberrant tissue. The digital findings validate the efficacy of the suggested method by showing improved sensitivity (92%), specificity (98%) and accuracy (97.93%) in differentiating between aberrant and normal tissue from brain MRI images.

Lastly, the innovations in image preprocessing techniques discussed by Chakraverti *et al.,* [22] were improved, demonstrating better performance metrics compared to conventional methods. The experimental findings demonstrate improved performance for certain key parameters (used by the current technologies). The work is innovative in the field of image preprocessing because, to dynamically choose the right block sizes during preprocessing, we categorize the image depending on its attributes. When it comes to PSNR, MSE, NRMSE, SSIM and SYNTROPY, the suggested work performs better. In comparison to CLAHE and LCM CLAHE, the average values involved are 18.92, 863.86, 0.25, 0.81 and 19.35, which are better.

A comprehensive case study by Chandrasekaran *et al.,* [23] is presented for a newborn diagnosed with the SCT (Sacrococcygeal teratoma) detection. The proposed method used medical image modalities to underscore the importance of prenatal detection using ultrasound and MRI, along for the early prenatal detection and plan for surgical intervention. Despite the SCT being mainly benign, the report emphasized the morbidity and mortality associated with complications such as hydrops fetalis, preterm labour and cardiac failure in cases of large or highly vascular tumours. The concluded remarks introduced the challenges in imaging SCT and highlighted the multidisciplinary ways for improving prediction.

Image processing modalities are used in many fields and of these field is healthcare. The study by Suhaili *et al.,* [24] focused on implanting FPGA (Field Programmable Gate Array) technology due to its ability to perform parallel pipelining and faster processing. The author used and tested five image techniques with FGPA technology (grayscale conversation, brightness method, contrast adjustment, threshold and inversion). The results show that FPGA technology is efficient for real-time application, such as medical imaging and surveillance. The programming tools such as Intel Quartus II, ModelSim Altera and MATLAB for design and simulation. FPGAs is used in image processing tasks for reduced processing times. The concluded remarks prove that the use of FPGA technology is improving diagnostic and real-time decision-making.

These studies demonstrate the effectiveness of transfer learning approaches and deep neural networks in various domains, including brain tumour classification, pneumonia detection, brain abnormality classification, disease classification and ECG monitoring. They provide valuable insights and methodologies that can be applied in the proposed research project on image classification in healthcare systems.

3. Methodology

The proposed system includes several phases for the detection and classification of brain tumours using CNN and Transfer Learning to be able to perform the task of Computer Deep Transfer Learning Approach for Healthcare Applications as shown in Figure 1. It initiates with data preprocessing, applying data augmentation to MRI scans of brain tissues and tumours to enhance diversity within the training dataset. After that, the dataset is divided into training and testing sets. This system utilizes a DenseNet-121 architecture that is pre-trained, customizing its classification head and compiles the model for training. It utilizes callbacks for monitoring and optimizing performance. Next, the model's performance is evaluated and a classification report is generated. Finally, we evaluate model performance and produce a classification report. Also, we displayed the mislabelled images to reveal and make clearly apparent results of the model’s inability to perform as expected. In addition, a sample set derived from this random cluster was also shown as inferred labelled random. In conclusion, the system's performance to detect and classify brain tumours accurately is a reliable and complete solution incorporating advanced deep learning transfer techniques.

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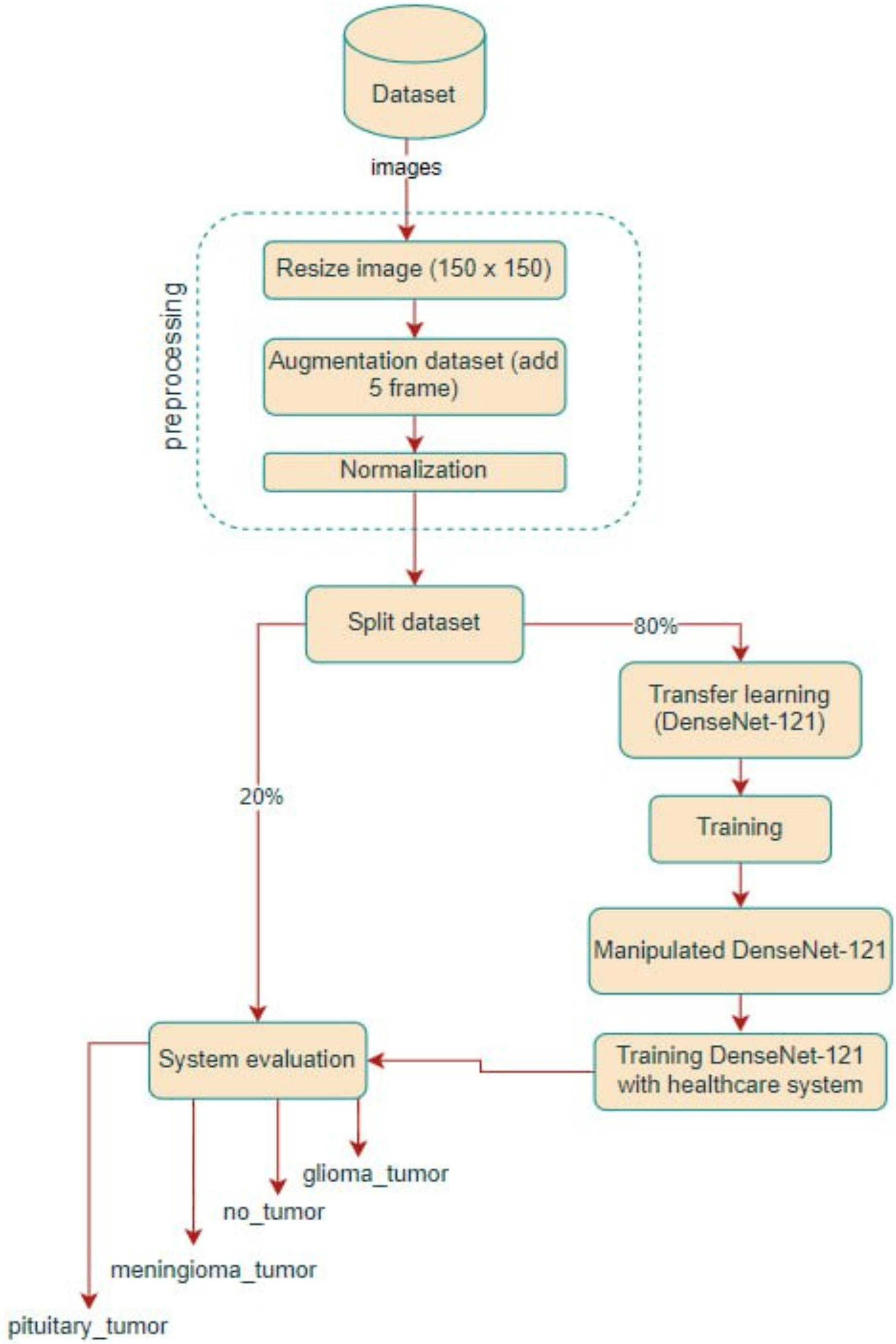

Fig. 1. The proposed system methodology

3.1 Dataset

The dataset utilized in this work is essential to improving the detection and classification of brain tumours using deep learning and advanced machine learning techniques, which focus on CNN and transfer learning. It includes many important elements, such as overall tumour classification data, MRI scans showing brain tissues and tumours and segmentation information for tumour location. These elements work together to provide the basic components needed to develop deep learning models that can effectively and precisely identify and categorize brain tumours. The dataset standard partitioning consists of 2,870 images for training and 394 for testing.

3.2 Pre-Processing

In this phase of the proposed system, we used three stages of preprocessing namely: First, by altering and modifying the original images, the data augmentation technique is used to increase the diversity of the dataset. Various image enhancements, including rotation, movement, scaling and other adjustments that increase diversity, are used in this technique. Then, the cv2.resize function is used to resize the images to 150 × 150 pixels, standardizing their size so that the model to be trained may utilize them. Finally, the shuffle ( ) function is used to randomly group the data, preventing a particular image arrangement and increasing arrangement diversity.

3.3 Dataset splitting

As shown in Figure 2, 80% of the images are used for model training and 20% are used for validating and testing the proposed system. This procedure, which is standard in deep learning and machine learning workflows, helps guarantee the accuracy and generalizability of the model.

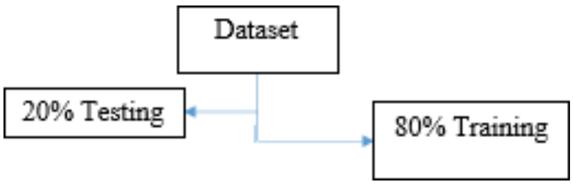

Fig. 2. Dataset division into train and test set

3.4 Train Model

In this stage, the transfer deep learning model (DenseNet-121) is trained using 80% of the data from the dataset mentioned in section 3.1.

3.5 Test Model

After completing the training process, the model is prepared to identify and classify medical images of brain tumours. To obtain unbiased outcomes, a separate test dataset is preserved which makes up 20% of the whole dataset. Testing the ability of the model to generalize is very critical at this point to obtain accurate outcomes. Achieving such results on the model’s accuracy is possible by using the trained model to the test dataset after the training process

4. Results and Discussion

The proposed DenseNet-121 model has been trained for the analysis and classification of Magnetic Resonance Imaging (MRI) with a specific focus on identifying brain tissues and tumours. By utilizing a pre-trained model equipped with knowledge from a diverse set of MRI image examples, the model has gained the capability to extract distinctive features that represent crucial elements within tissues and tumours. These extracted features are subsequently employed to differentiate between normal tissues and pathological tumours in the images. This section presents the results of these efforts and discusses their implications.

Figure 3 shows the types the images in the dataset that contain four types of brain tumours, including glioma, meningioma, pituitary tumour and also images without any tumours. The file size is 93.08 MB.

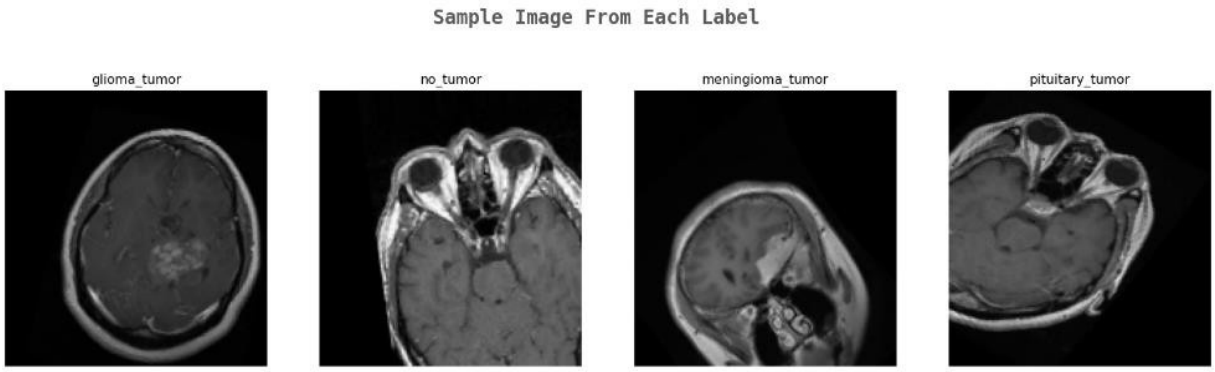

Fig. 3. Tumour classes images in the dataset

Figure 4 to Figure 8 show the deep learning model's training process for 20 epochs, which was used to identify and classify brain tumours using the suggested approach. We noticed the accuracy of training is 99.98%, which indicates that the model learned the training data exceptionally well. Additionally, system performance is evaluated on unseen data by measuring the validation accuracy, which was approximately 98.72%. The learning rate was lowered using the ReducLROnPlateau callback to enhance performance. The loss values of training and validation are low, indicating that the system was effective in minimizing the loss function. However, the system is tested on a separate dataset, resulting in an accuracy of 99%. The classification report provided detailed metrics (such as Recall, precision and F1 score) for each class, which demonstrated the system good performance in detecting and classifying brain tumours.

	Epoch	Accuracy	Loss	Val_Accuracy	Val_Loss	Learning_Rate
0	1	0.7245	0.8645	0.6612	2.7428	0.001000
1	2	0.9081	0.2712	0.6156	1.7590	0.001000
2	3	0.9329	0.1996	0.6824	1.1198	0.001000
3	4	0.9327	0.1943	0.8534	0.5092	0.001000
4	5	0.9552	0.1236	0.6889	1.1503	0.001000
5	6	0.9645	0.1080	0.8632	0.4601	0.001000
6	7	0.9661	0.0982	0.9316	0.2203	0.001000
7	8	0.9647	0.1181	0.8681	0.4485	0.001000
8	9	0.9757	0.0751	0.9088	0.3687	0.001000
9	10	0.9887	0.0350	0.9739	0.0770	0.000300
10	11	0.9966	0.0118	0.9821	0.0523	0.000300
11	12	0.9986	0.0079	0.9837	0.0573	0.000300
12	13	0.9988	0.0085	0.9739	0.0830	0.000300
13	14	0.9991	0.0041	0.9788	0.0595	0.000300
14	15	0.9985	0.0045	0.9837	0.0517	0.000090
15	16	0.9996	0.0018	0.9837	0.0502	0.000090
16	17	0.9997	0.0018	0.9821	0.0506	0.000027
17	18	0.9995	0.0027	0.9837	0.0529	0.000027
18	19	0.9999	0.0016	0.9837	0.0523	0.000008
19	20	0.9990	0.0040	0.9837	0.0521	0.000008

Fig. 4. The train phase

	precision	recall	f1-score	support
0	0.99	0.99	0.99	406
1	0.98	1.00	0.99	314
2	0.98	0.96	0.97	384
3	0.99	0.99	0.99	430
accuracy			0.98	1534
macro avg	0.98	0.98	0.98	1534
weighted avg	0.98	0.98	0.98	1534

Fig. 5. Confusion matrix report

Fig. 6. Training and testing accuracy

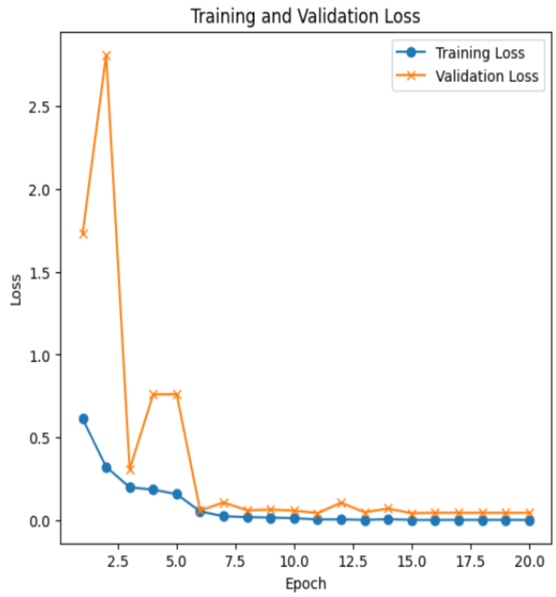

Fig. 7. Training and testing accuracy

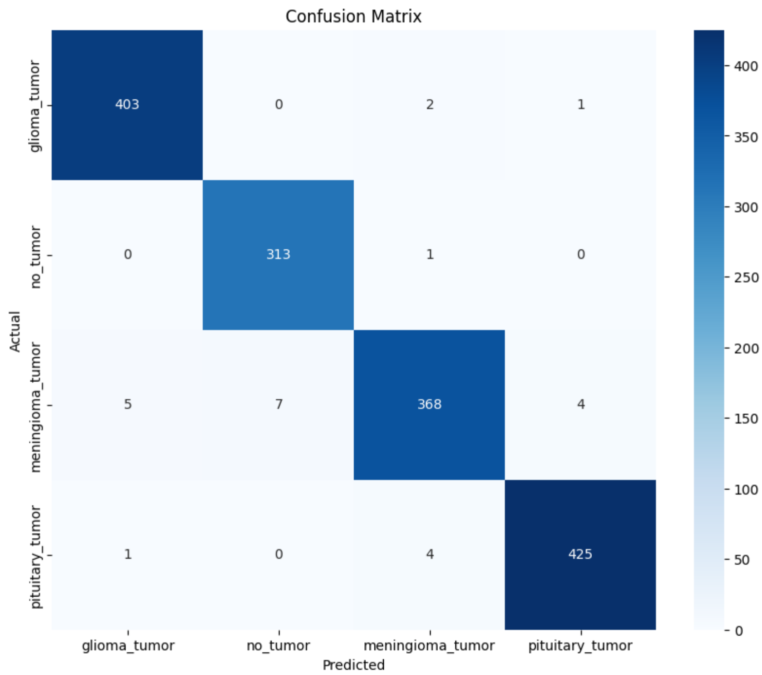

Fig. 8. The confusion matrix

In order to verify the performance of the system, we randomly selected images from the test set, as shown in Figure 9. We noticed the results were accurate, as the deep learning transfer system presented in this work was able to predict with remarkable accuracy. Subsequently, we compare our proposed system against many state-of-the-art approaches, we notice that our model excels in detecting medical images using transfer deep learning with an accuracy of 99 %.

Fig. 9. The predict phase of tumour detection

Table 1 shows a comparison of the experimental results obtained from the proposed system with state-of-the-art approaches mentioned in Section 2.

Table 1
Comparison between a proposed system work and other work

No	Name	Year	Accuracy %	Algorithm
1	Our proposed system	2024	99 %	Transfer deep learning DenseNet-121
2	Hidayatullah *et al.,* [28]	2020	98.24%.	VGG16
4	Saba *et al.,* [26]	2020	86%	Mobile Net
			95%	VGG-19
5	Chen *et al.,* [27]	2020	98.8%	Fed Health
			95.5%	No Fed
6	Dawud *et al.,* [15]	2019	93.48%	Alex Net-SVM
			92.13%	Alex Net

5. Conclusion

Our study developed a comprehensive approach for constructing and evaluating a brain tumour classification model using transfer deep learning techniques. We found that a well-structured with dataset of 2,870 training images and 394 testing images. that includes MRI scans, tumour classification, location segmentation and augmented data is critical for robust model training and evaluation. We also utilized transfer learning, specifically employing the DenseNet121 architecture with pre-trained weights from ImageNet, which allowed our model to leverage pre-existing knowledge from a diverse range of MRI images. The model demonstrated a 99.98% training accuracy, which is almost optimal. Furthermore, the model achieved an approximately 98.72% validation accuracy and thus has generalized well on unseen data without causing the loss function to grow during training. As discussed, our model was evaluated by independent test data and achieved an approximately 99% accuracy and displayed other metrics, such as precision, recall and F1 score. The results show that the model is also superior in terms of detection and classification of brain tumours. Finally, based on the comparison and analysis of previous studies, the proposed model has a 99% accurate figure. This indicates the highest level of accuracy in the past, compared to other existing methods of medical image classification. Further, such a system can further be studied on one analysing other medical images.

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