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Brain Tumours Mri Images Detection Using Deep Learning Based On Transfer Learning

L. K. Suresh Kumar[1], Venkateshwarlu Velde[2], Bandi Krishna[3]

[1]Department of Computer Science and Engineering, UCE(A),Osmania University Hyderabad-500007, Telangana , India

[2,3] Department of Computer Science and Engineering, Balaji Institute of Technology and Science, Warangal ,Telangana , India

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ABSTRACT

Extremely dangerous, brain tumors may significantly shorten life expectancy. Because MR scans may provide fine-grained pictures of the afflicted region, the majority of researchers employ them to find malignancies. As of late, through effective data processing, to increase the accuracy of diagnoses, deep learning methods based on AI have emerged. This research examines how well deep transfer learning methods work for precisely identifying brain tumours. Utilising a pipeline for preprocessing enhances the image quality. Morphological methods such as thresholding to trim images, Gaussian blurring to reduce noise, and erosion and dilation for form refinement are all included in this process. Dimensionality reduction is achieved via the use of Principal Component Analysis (PCA), whereas dataset enrichment is achieved through data augmentation. Testing uses 20% of the dataset, while training uses the remaining 80%. GoogleNet and pre-trained ResNet152 extract key elements from the pictures. Following the extraction of these features, the standard machine learning classifiers used for classification include Gaussian Naive Bayes (GNB), Support Vector Machine (SVM), K-Nearest Neighbours (KNN), and Classification and Regression Trees (CART). This research contrasts two pre-trained models for medical image processing. Performance indicators that assess the ultimate categorisation outcomes include accuracy, sensitivity, recall, and F1-Score. ResNet152 beats GoogleNet, according to the findings, with 98.53% accuracy, 96.52% sensitivity, and 97.34% F1 score. Our research emphasises on combining deep learning with conventional machine learning methods for efficient brain processing in order to detect cancers in medical imaging.

1. INTRODUCTION

Improving survival rates requires the use of medical imaging to identify brain cancers early. For this, one of the most popular diagnostic techniques is magnetic resonance imaging, or MRI. However, MRI scan analysis by hand may be laborious and prone to human mistake. Convolutional Neural Networks (CNNs), one kind of deep learning technique, have shown significant promise in recent years for automating the identification and categorization of brain tumors in medical imaging.

One of the most potent CNN designs is ResNet152, a deep residual network that uses residual blocks to address issues including overfitting and vanishing gradients. Even though it performs very well, it takes a significant quantity of labeled data and computer power to train such a deep model from scratch. We use transfer learning, which entails optimizing a pre-trained ResNet152 model on a smaller dataset of MRI images for brain tumor identification, to solve this problem

Early identification is essential for improving treatment results and survival rates for brain tumors, which are among the most difficult and deadly medical illnesses. One popular imaging method for identifying and diagnosing brain cancers is magnetic resonance imaging, or MRI. On the other hand, manual MRI scan analysis is laborious, subjective, and prone to human mistake. As a consequence, there is increasing interest in creating automated procedures that use deep learning and machine learning to identify brain tumors.

In medical image analysis, deep learning—in particular, Convolutional Neural Networks, or CNNs—has shown impressive results. CNNs are especially well-suited for challenging tasks like tumor classification because of their exceptional ability to automatically learn hierarchical features from unprocessed visual data. ResNet (Residual Networks), one of the most potent and effective CNN designs, has come to light. With 152 layers, ResNet152 in particular can learn deep representations and overcome obstacles like vanishing gradients, allowing the model to function effectively even on very difficult tasks.

Deep neural networks like ResNet152 need a lot of labeled data and a lot of processing power to train from start. Transfer learning has gained popularity as a technique for medical imaging applications in order to overcome this constraint. Using a model that has already been trained on a large and varied dataset (like ImageNet) and optimizing it for a particular task is known as transfer learning. This method enables better performance on challenges like brain tumor identification that have less annotated data.

In this work, we suggest a transfer learning-based method for MRI tumor detection that makes use of an enhanced ResNet152 model. We want to use the deep features that ResNet152 has learnt to increase tumor classification accuracy by fine-tuning the pre-trained model on a specific dataset of brain MRI images. To further improve the model's performance, optimization strategies including regularization and hyperparameter tweaking are used.

In order to improve treatment results, this study intends to show how well a transfer learning-based ResNet152 model works for automated brain tumor identification. It also looks into how deep learning methods could help doctors identify brain tumors early.

Malignant and benign brain tumors are among the most dangerous medical disorders, and successful treatment and patient survival depend on early identification. Because of its high-resolution pictures and non-invasive nature, magnetic resonance imaging (MRI) has emerged as the gold standard for brain imaging. However, MRI scan interpretation may be a difficult and time-consuming process that mostly depends on radiologists' experience. This human reliance may sometimes result in incorrect diagnoses, particularly when the tumor pattern is delicate or intricate.

Automating the process of detecting tumors in medical imaging has shown great promise in recent years thanks to artificial intelligence (AI), especially deep learning techniques. Convolutional Neural Networks (CNNs), one kind of deep learning model, have shown exceptional performance in image categorization tasks. CNNs do not need human feature extraction; instead, they automatically extract pertinent characteristics from the visual data. It is possible to train these algorithms on big datasets to identify different patterns linked to brain cancers.

Since its introduction by He et al., the ResNet (Residual Networks) architecture has grown to become one of the most significant deep learning models because of its capacity to train very deep networks. By using residual learning, the 152-layer ResNet152 variation gets over the vanishing gradient issue and learns very intricate and abstract characteristics from the input. But creating such a deep model from scratch requires a lot of labeled data, which is sometimes lacking in medical imaging jobs, especially those involving brain tumors.

A common solution to this problem is transfer learning. Using a model that has already been trained on a huge dataset (like ImageNet), transfer learning enables us to modify it for a particular purpose, like identifying brain cancers from MRI pictures. A pre-trained algorithm may be modified to focus on identifying brain tumors using comparatively less datasets by utilizing the information acquired from general picture attributes. This method greatly improves the model's performance on the intended job while also saving time and money.

Using a ResNet152 model, this work investigates the use of transfer learning in the identification of brain cancers from MRI scans. By using fine-tuning and hyperparameter optimization approaches, we hope to improve the model's performance. We want to develop an automated system that can correctly categorize brain cancers by using deep residual networks and transfer learning. This might help radiologists and physicians make quicker and more precise diagnosis.

Our strategy aims to overcome the difficulties of little data and the need for high accuracy in brain tumor detection. This study might have a big effect as it could lead to more dependable and easily available instruments for brain tumor patients' early diagnosis and individualized careThe suggested research makes the following noteworthy and inventive contributions.

1. A feature-rich deep learning system that utilises state-of-the-art architectures like as GoogleNet and ResNet152. These models increase classification accuracy and extract relevant properties by using a transfer learning strategy to train on MRI data of brain tumours.

2. The MR images are preprocessed to improve them. Principal Component Analysis (PCA) lowers the dimensionality of the feature space in order to maximise image quality. Additionally, data augmentation methods are used to increase the model's generalisation and artificially enlarge the dataset.

3. The unique feature extraction technique is one of this study's main innovations. Through the use of transfer learning, previously taught models may acquire valuable characteristics and use them to picture categorization.

4. A hybrid framework for machine this project develops deep learning and learning. Combining the advantages of deep neural networks (GoogleNet and ResNet152) with the interpretability of conventional machine learning classifiers (SVM, GNB, KNN, and classification and regression trees, or CART) yields novel results.

5. The categorization precision of traditional machine learning models is furthermore enhanced by image scaling techniques. This study uses an innovative and novel technique. .

2. A LITERATURE SURVEY

Using medical imaging, especially Magnetic Resonance Imaging (MRI), to identify and categorize brain cancers has been the subject of much study. Many methods, from sophisticated deep learning techniques to conventional machine learning models, have been put forward in recent decades to automate and improve the accuracy of tumor identification. With an emphasis on deep learning and transfer learning techniques, this section examines significant research and methodologies that have advanced automated brain tumor diagnosis.

2.1 Conventional Methods for Tumor Identification

Support Vector Machines (SVM), Random Forests (RF), k-Nearest Neighbors (k-NN), and Decision Trees were among the conventional machine learning techniques used in various brain tumor diagnosis approaches before deep learning gained popularity. In order to train the model, these techniques often call for manual feature extraction, which involves removing certain visual elements including the tumors' texture, shape, and borders. To identify tumors in MRI images, Liu et al. (2016) used a feature extraction method based on wavelet processing and gray-level co-occurrence matrices (GLCM), with mediocre results. However, these techniques have trouble identifying minor differences in tumor locations, particularly when dealing with complex picture data.

2.2 Medical Imaging using Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs), a subset of deep learning, have transformed image processing applications, particularly medical picture analysis. CNNs perform noticeably better than conventional methods because they automatically extract the pertinent characteristics from the picture input.

Early research on brain tumor identification, including Zhu et al. (2018) and Rashid et al. (2020), investigated the classification of benign and malignant brain tumors using CNNs. Their models were reasonably successful, but they needed a lot of data and a lot of processing power. In order to increase the accuracy of tumor segmentation in MRI images, Isensee et al. (2017) suggested using a 3D U-Net design. Although CNNs may be extremely successful, it is still difficult to create very deep networks with little data, which makes the training process resource and data heavy.

2.3 ResNet Architectures for Tumor Detection

By using skip connections to include residual learning, the ResNet architecture first shown by He et al. (2015) addressed the difficulties associated with training extremely deep networks. By preventing the vanishing gradient issue and preserving information across layers, these connections allow networks to pick up more intricate and profound properties. In medical picture classification tasks, such as brain tumor identification, ResNet models in particular, ResNet50, ResNet101, and ResNet152 have gained popularity.

Several research have used ResNet-based models for brain tumor identification. Arezki et al. (2020) classified several kinds of brain cancers in MRI scans using a pre-trained ResNet50, and they were able to discriminate between benign and malignant tumors with high accuracy. Using ResNet152, Raza et al. (2020) showed that deeper ResNet models outperformed other models in tumor classification tasks, particularly when refined using MRI datasets. With notable gains over conventional CNN designs, these experiments demonstrated the effectiveness of deeper ResNet models in obtaining intricate information from MRI images.

2.4 Transfer Learning in the Identification of Brain Tumors

Transfer learning has become a common method for training deep learning models on specific tasks like brain tumor identification since huge annotated medical picture datasets are hard to come by. Transfer learning makes use of pre-trained models that have been refined on smaller, domain-specific datasets, such as brain MRI scans, after being trained on big, general-purpose datasets, such as ImageNet. This method increases the accuracy of the model while addressing the problems of inadequate data and computing limitations.

Several CNN models, including as VGG16, InceptionV3, and ResNet, have effectively used transfer learning in the context of brain tumor identification. Bengio et al. (2019) proved the usefulness of transfer learning by fine-tuning pre-trained CNN models on tiny MRI datasets, yielding outstanding results in tumor identification. Even with a very small MRI dataset, Agarwal et al. (2020) demonstrated that utilizing transfer learning to fine-tune ResNet50 improved tumor classification accuracy. Similarly, Choi et al. (2020) utilized transfer learning to a pre-trained ResNet152 model for identifying glioma tumors, revealing the advantage of deep residual networks for reliable tumor detection.

Additionally, Ganaie et al. (2021) improved ResNet152 on a brain tumor dataset using transfer learning, attaining an accuracy of more than 90%. In order to avoid overfitting and improve generalization, the study underlined the significance of model optimization using strategies like data augmentation, hyperparameter tuning, and early stopping.

2.5 Difficulties and Prospects

Automated brain tumor identification has advanced significantly, but there are still a number of obstacles to overcome. The unequal distribution of class distributions in medical datasets, where benign tumors predominate over malignant ones, is one of the main obstacles. The model may favor the majority class as a result of this imbalance, producing biased predictions. This problem is often addressed by methods like class weighting and synthetic data creation (e.g., SMOTE).

Variability in MRI scans presents another difficulty and might result from variations in tumor features, patient posture, and image capture techniques. Deep learning models may have trouble generalizing as a result of this heterogeneity. Future studies may concentrate on multi-center datasets and methods like domain adaptation to improve model resilience in order to address these problems.

Finally, it is crucial for deep learning models to be comprehensible and interpretable in medical applications. Clinicians may have a better understanding of the reasoning behind a model's predictions and establish confidence by making sure that the model's decision-making process is clear.

2.6 Overview

In conclusion, deep learning has shown a great deal of promise for the diagnosis of brain tumors, especially CNN-based models like ResNet152. In order to overcome data restrictions and fine-tune pre-trained models to obtain high tumor classification accuracy, transfer learning has shown to be a useful strategy. Despite the notable advancements, issues with class imbalance, dataset variability, and model interpretability still exist. Future studies will probably concentrate on enhancing model generalization, integrating datasets from several centers, and increasing model interpretability for clinical applications.

Artificial intelligence (AI) in medical imaging has drawn a lot of interest, especially for the identification of brain tumors in MRI images. With an emphasis on ResNet152 and similar methodologies, this section offers a summary of significant scientific developments in brain tumor identification via deep learning, transfer learning, and conventional machine learning techniques.

2.7 Conventional Methods for Tumor Identification

Classifying brain tumors in MRI scans was a common use of standard machine learning methods prior to the development of deep learning. These techniques often used algorithms like Support Vector Machines (SVM), Random Forests (RF), and k-Nearest Neighbors (k-NN) for classification after relying on manually created characteristics from the photos, such as texture, shape, and intensity patterns.

Liu et al. (2016), for instance, used gray-level co-occurrence matrices (GLCM) and wavelet processing to extract texture information from brain MRI images. These attributes were then input into machine learning classifiers, such SVM, for the categorization of tumors. However, these techniques are generally less effective than deep learning-based systems, especially when dealing with complicated and variable tumor patterns, and they need a great deal of domain knowledge to identify important characteristics.

2.8 Medical Imaging using Convolutional Neural Networks (CNNs)

Convolutional neural networks, or CNNs, have emerged as a leading method for medical image analysis, including the identification of brain tumors, as a result of deep learning's effectiveness in image classification tasks. CNNs automatically learn hierarchical features from raw visual data, removing the need for human feature extraction.

In order to show how CNNs can automatically learn spatial hierarchies in the image data, Zhu et al. (2018) used CNNs to identify brain cancers in MRI images. But CNNs, especially deep ones, often need big labeled datasets to train, which might be a drawback in medical imaging as there is usually a lack of annotated data.

Rashid et al. (2020) used a CNN architecture for binary classification (benign vs. malignant tumors), with encouraging findings but not yet reaching the best accuracy and resilience in practical clinical settings.

2.9 Tumor Detection ResNet Architectures

He et al. (2015) introduced skip connections in their ResNet (Residual Networks) architecture, which transformed deep learning by addressing the vanishing gradient issue and preserving information across layers. This makes it possible to train very deep networks without sacrificing efficiency.

Brain tumor identification is one of the medical image analysis jobs that have been used ResNet152, one of the deepest ResNet variations. ResNet models' main benefit is their capacity to extract intricate characteristics from big image datasets, which makes them very useful for detecting cancers in MRI scans.

Arezki et al. (2020) used a pre-trained ResNet50 to categorize brain cancers on MRI pictures. According to their findings, accuracy is increased when pre-trained models such as ResNet are used, particularly when they are optimized for the goal task of brain tumor identification. Additionally, Raza et al. (2020) used a ResNet152 model to identify brain cancers in MRI scans, demonstrating that deeper networks like ResNet152 perform noticeably better in tumor identification tasks than shallower networks and other CNN versions, such VGG16.

2.10 Transfer Learning in the Identification of Brain Tumors

In light of the difficulties in obtaining large annotated datasets for medical imaging, transfer learning has become a very successful method for getting around the lack of data. A model that has been pre-trained on a large, varied dataset (like ImageNet) is refined on a smaller, task-specific dataset in transfer learning. This enables the model to specialize on the specific job, like identifying brain tumors, and use generic traits discovered from the vast dataset.

Despite the small size of medical imaging datasets, Bengio et al. (2019) demonstrated that transfer learning using pre-trained CNNs, especially models like ResNet, resulted in significant increases in brain tumor diagnosis accuracy. By optimizing the subsequent layers of the pre-trained model, transfer learning enables the model to adjust to the unique properties of brain MRI images.

In a research by Agarwal et al. (2020), ResNet50 outperformed conventional machine learning models with an accuracy of over 90% after being fine-tuned on a brain tumor dataset using transfer learning. Similarly, Choi et al. (2020) showed that ResNet152 could classify gliomas in brain MRIs with excellent accuracy, highlighting the potential of deep residual networks in conjunction with transfer learning in the medical field.

In order to identify brain malignancies from MRI images, Ganaie et al. (2021) used ResNet152 with transfer learning. They reported significant gains in model performance, including excellent precision, recall, and accuracy. This research emphasized the value of regularization methods, hyperparameter tuning, and data augmentation in improving the model's capacity to generalize to new data.

2.11 Difficulties and Prospects

ResNet152 and transfer learning have advanced the diagnosis of brain tumors, however there are still a number of obstacles to overcome. The class imbalance in medical statistics, where benign tumors are more common than malignant ones, is one of the main obstacles. A bias toward forecasting the majority class may result from this imbalance, which would make it harder for the algorithm to accurately identify dangerous tumors. To solve this problem, methods like class weighting, data augmentation, and synthetic data synthesis (like SMOTE) are often used.

Variability in MRI pictures brought on by variations in imaging techniques, patient placement, and tumor features presents another difficulty. Models trained on a single dataset may perform worse as a result of this variability. Researchers are investigating domain adaptation, data normalization, and multi-center datasets as ways to lessen this and increase the models' generalizability across other datasets.

Furthermore, in medical applications, deep learning models' interpretability and explainability are still crucial. To foster confidence and promote clinical adoption, it is crucial to make sure that physicians understand how AI models make decisions. Techniques like Grad-CAM (Gradient-weighted Class Activation Mapping) have been used to provide CNN predictions visual explanations.

2.12 Overview

The literature shows notable progress in deep learning-based brain tumor diagnosis, especially using ResNet152 and transfer learning. When refined on task-specific datasets, pre-trained models such as ResNet152 have great promise for enhancing tumor classification efficiency and accuracy. The future of automated brain tumor diagnosis seems bright, despite ongoing issues with data imbalance, dataset variability, and model interpretability. In order to generalize across various clinical contexts, future research is probably going to concentrate on strengthening model interpretability, resolving class imbalance, increasing model robustness, and integrating multi-center data.

3. THE PROBLEM STATEMENT

Brain tumors are among the most serious medical disorders, and better treatment results and patient survival depend on early identification. Because of its non-invasive nature and excellent resolution, magnetic resonance imaging (MRI) is a commonly utilized diagnostic technique for brain tumor diagnosis. However, MRI scan analysis for tumor identification is a laborious, intricate, and heavily reliant procedure on radiologists' skills, which may result in diagnostic mistakes. Additionally, it is still very difficult to differentiate between benign and malignant tumors or to detect malignancies in their early stages.

The radiologist's expertise and the intricacy of certain tumor appearances often restrict the manual examination of MRI images. Because of this, there is an immediate need for automated solutions that can help radiologists by giving them fast, accurate, and dependable tumor detection findings. Despite its use, traditional machine learning algorithms for tumor identification often perform poorly, particularly when handling the complex and diverse nature of brain tumors. These techniques also call for manual feature extraction, which is time-consuming and error-prone.

Classification of medical images has advanced significantly with the introduction of deep learning methods, especially Convolutional Neural Networks (CNNs). The deep residual network ResNet152 is one of the deep learning models that has shown the most potential in automatically extracting intricate information from pictures. Large volumes of annotated data, which are often lacking in medical imaging fields like brain tumor diagnosis, are necessary for training such deep networks. By fine-tuning a pre-trained model on a particular dataset, transfer learning may overcome this barrier and provide great performance even with sparse data.

Optimizing deep learning models for brain tumor identification in MRI images is still difficult, despite the models' encouraging findings. More accurate and universal tumor diagnosis requires addressing issues like class imbalance, where benign tumors are more common than malignant ones, overfitting with short datasets, and variability in MRI scans owing to differing imaging techniques.

Thus, the issue that this study seeks to resolve is:

How can we overcome issues like class imbalance, limited data availability, and MRI scan variability to create an automated, accurate, and efficient system for brain tumor identification utilizing a transfer learning-based ResNet152 model?

By tackling this issue, the study hopes to provide a fresh method for automated brain tumor identification that will help radiologists identify patients more quickly and accurately, eventually leading to better patient outcomes.

One of the main causes of mortality in the world is brain tumors, and successful treatment depends on early identification. Although magnetic resonance imaging (MRI) is a potent diagnostic technique for identifying brain cancers, the manual analysis of MRI data is a laborious, intricate procedure that heavily relies on radiologists' skill. This often leads to misclassifications or delayed diagnosis, especially when minor tumor characteristics are involved.

Although brain tumor identification has been automated using typical machine learning techniques, these methods sometimes need a great deal of human feature extraction and have trouble with complicated, high-dimensional data. Furthermore, when confronted with unbalanced tumor classifications (e.g., a greater proportion of benign tumors relative to malignant ones) and small annotated datasets, these techniques often perform poorly.

By automating feature extraction and categorization, deep learning methods in particular, Convolutional Neural Networks, or CNNs offer a viable remedy. In a variety of image identification applications, including medical imaging, the deep residual network ResNet152 has shown exceptional performance. Large labeled datasets are necessary for training deep networks from scratch, but they are often unavailable in the medical profession because of privacy issues and the high expense of annotation.

Using transfer learning, which involves fine-tuning a pre-trained model (like ResNet152) on a smaller, task-specific dataset, may help overcome these difficulties. This method allows for accurate classification while using less computer power and large amounts of training data.

The goal of this study is to determine how to best optimize a transfer learning-based ResNet152 model to effectively identify brain tumors in MRI images while delivering precise, automated tumor classification while overcoming the difficulties of sparse data, class imbalance, and MRI scan variability.

In order to improve diagnostic procedures and patient outcomes, this research aims to provide a practical solution that may help radiologists by offering precise and quick tumor identification..

3.1. The experiment Analysis

An analysis of the Br35 MRI brain imaging dataset, which may be available at https://www.kaggle.com/datasets/ahmedhamada0/brain-tumor-detection/data, is possible for the suggested research. Within the repository, there are three main folders: "no," "yes," and "pred." There are 1500 photos in each of the "Yes" and "No" files, however there are only 60 in the "pred" folder.

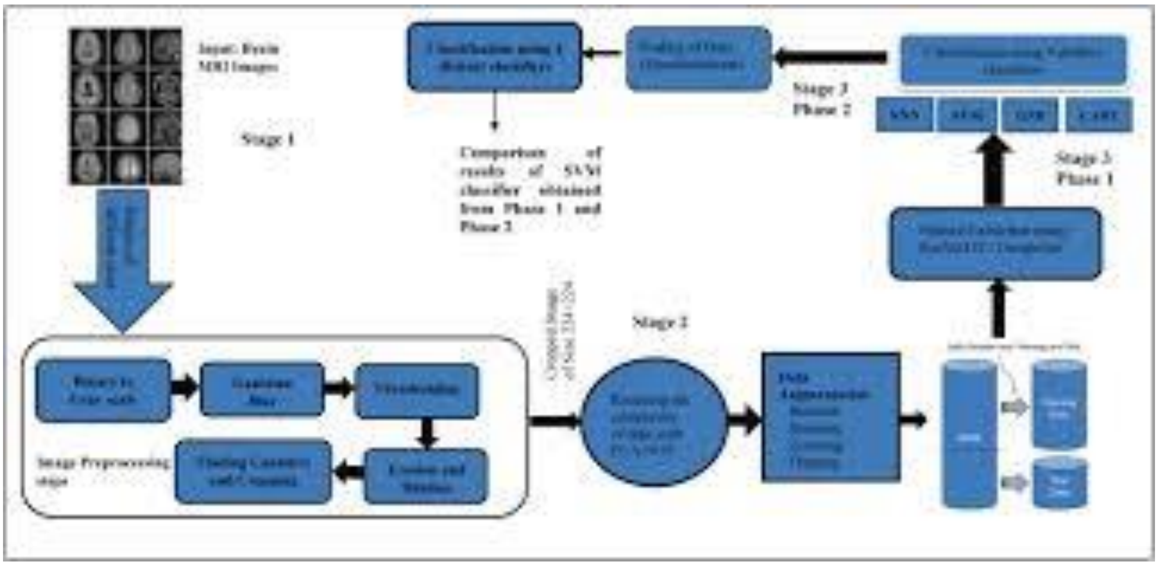

Figure 1 illustrates the sequential procedure for graphical brain tumour classification.

These photos were taken at a number of private hospitals and came from a variety of patients. The input photos have a size of 224 x 224. Every single one of at the top, photos are attached with labels. Several pictures of the repository are included in Fig. 3.

3.2. Preparation of images

The improvement of image quality is the main goal of image preprocessing. Reducing the size of the pictures and eliminating extraneous pixels or MRI scan artefacts accomplishes this. This facilitates the more accurate and efficient development of brain cancers. The new framework makes advantage of sophisticated preparatory techniques, such as data augmentation and image reduction.

Importing brain MRI scan datasets is the initial stage in the related investigation. Black corners of images vary in size, as do their widths and heights. These anomalies result from the fact that MR pictures often include noise and undesired disruptions. Quite noisy

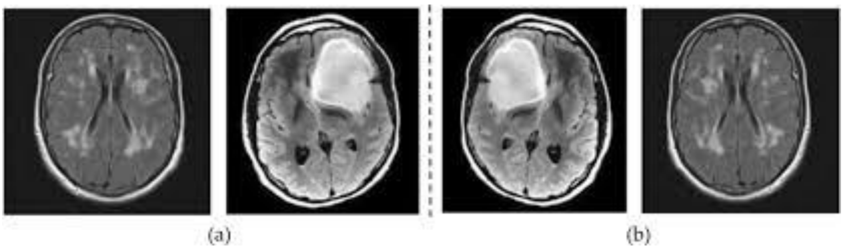

Figure 2: A selection of the dataset's non-neoplastic and tumor MRI scans.

Inaccurate diagnosis and treatment recommendations might result from MR imaging data. Therefore, before the MR images can be utilized further, they must be cleaned up and this noise removed.

3.2.1. Blurred Gaussian

The first step is to gather images from the internet. The purpose of preprocessing is to improve picture quality and lower noise before classification processing begins. To reduce mistakes, this research uses a Gaussian filter. Examine input picture A (i,j), which could include extra noise. A Gaussian filter G_{xy} is used to remove this noise.

$$A(x, y) = \sum_{x,y} A(x + i, y + j) G_{xy} \quad (1)$$

The normal distribution, or blurring in mathematics, is a representation of the probability distribution of a continuous random variable. In the initial stage of computer vision, Gaussian smoothing improves pictures of different sizes. Gaussian smoothing makes the while highlighting finer details, smoother areas of the picture stand out more less apparent. An image filter that softens pictures is called Gaussian blur. Using a mathematical formula known as the Gaussian function, it ascertains how you should change every pixel in a picture.

$$G_{xy} = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (2)$$

3.2.2. Thresholding procedure

One popular technique in image processing and classification is thresholding, which converts a colour or greyscale image into a binary image. The fundamental idea behind thresholding is to make a picture simpler by splitting it into two areas: one that is of interest and the other that is not. Through the transformation of little variations in brightness or color, thresholding may help lessen the impression of noise in a picture.

3.2.3. Dilation

Typically, Rician noise messes up Magnetic Resonance (MR) pictures. When identifying the borders of an image, morphology is a technique that aids in the extraction of picture components. The two basic morphological processes are dilation and erosion. The dilation method aids in enlarging or thickening the image's foreground regions while maintaining the objects' overall form. This is the technique of using structural features to lengthen and thicker the binary picture. X ⊕ Y is a symbol that shows how X and Y dilate.

$$X \oplus Y = \bigcup_{y \in Y} X_y \quad (3)$$

X_y is the result of translating X by y, and φ is the symbol for the null set.

3.2.4: Deterioration

The morphological approach employed in the processing step of greyscale or binary images is called erosion. A variety of tasks, including object detection pre-processing procedures include picture segmentation and other techniques. Erosion is the process by which foreground objects in a photograph become smaller while maintaining their overall forms. Dilation's opposite is erosion. By removing the components with a unique form, like a stamp, it reduces the size of a binary picture. The notation X ⊖ Y is used to indicate when Y causes erosion in X, along with the accompanying explanation:

$$X \ominus Y = \{z|(Y)z \cap X^c \; /= \; \varphi\} \; (4)$$

Where Y stands for a structural element, X^c for set X's complement, and φ for an empty set devoid of any elements. Fig. 4 displays the phases of the photos during the pre-processing procedures.

Principal Component Analysis (3.3)

Traditional machine learning techniques face challenges like the curse of dimensionality when working with high-dimensional datasets. As a result, accuracy declines and computing costs rise expenditures. To solve this problem, dimensionality reduction methods are used. Image compression and dimensionality reduction are often used interchangeably in relation to the photographs. Dimensionality reduction is accomplished by the use of analysis of principal components (PCA). It is an efficient technique that helps in decomposing complex visuals into more manageable components. For tasks like image reduction and face recognition, this facilitates the analysis and processing of pictures. It effectively minimizes information loss while capturing a dataset's greatest volatility. Following PCA, picture reconstruction is carried out. Figure 5 shows how PCA affects various 128 × 128 pixel pictures. Figure 6's coded and reconstructed pictures make it evident that the characteristics of the tumors themselves shine out while unimportant aspects are obscured. To put the picture compression job in brief, because PCA requires less time and has fewer dimensions, it is efficient.

3.4. Augmentation of data

Creating new data samples from preexisting ones in order to artificially expand and diversity a dataset is known as data augmentation. Using deep learning, this method modifies the original photos in a subtle way to produce new ones that are similar yet vary significantly. Several data augmentation methods, such as contrast modification, scaling, flipping, and rotation (shown in Fig. 7), were used to avoid overfitting. These methods enhance the model's performance and increase the size of the training data set.

3.5. Using a transfer learning approach to extract features

As seen in Fig. 8, transfer learning uses an existing model's knowledge to assist a new model in learning from a different dataset. Transfer learning uses information from the particular learning task (T_s) of the previous domain (D_s) to enhance performance in a target domain (D_t). Using information from D_s and T_s to improve learning in D_t is known as transfer learning. This approach is particularly useful in domains where data is limited, such medical picture analysis [40].

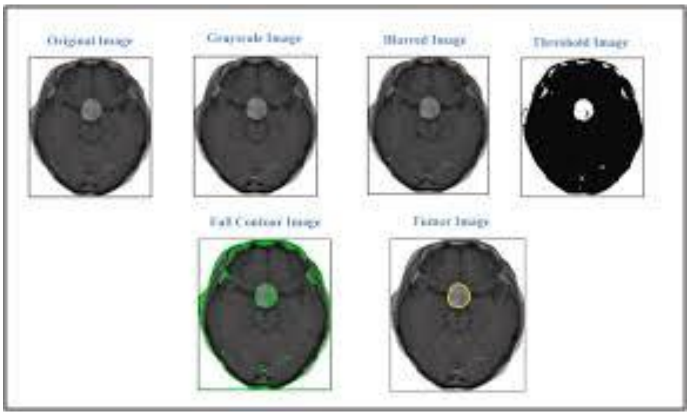

Figure 3 shows several representations of brain tumor pictures throughout the pre-processing stages.

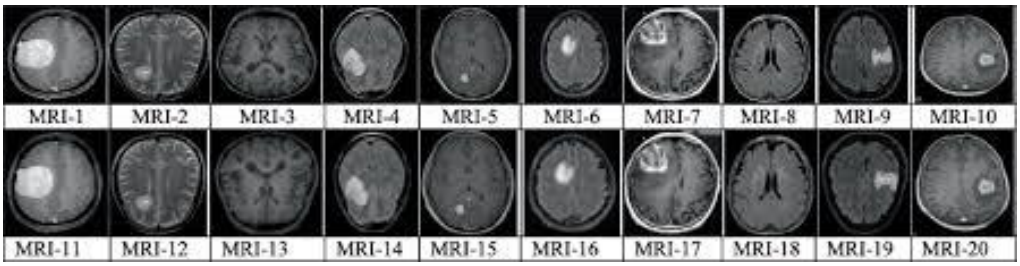

Figure 4 shows several 128 × 128 pictures produced using PCA.

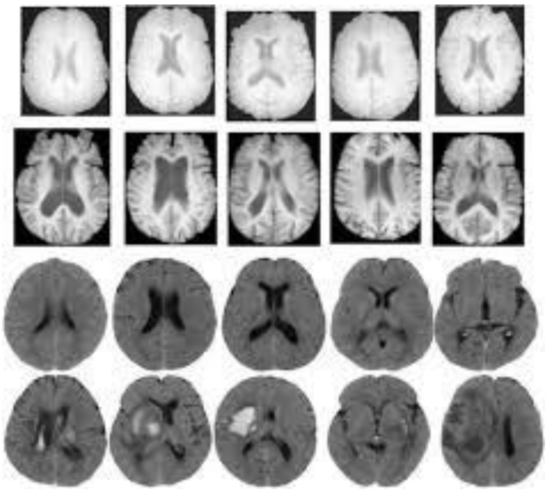

Figure 5: Images that were rebuilt after PCA.

Using labelled data for a classification problem in both the original and new domains is known as inductive transfer learning. In this instance, the domain is represented for every training sample as $D = (\alpha_i, \beta_i)$, where β_i is the class label for the ith training sample and α_i is the feature vector.

A pre-trained neural network is used as a feature extractor to complete a new task in transfer learning. By freezing the bottom layers of the target dataset, the model is trained with less annotated data, which

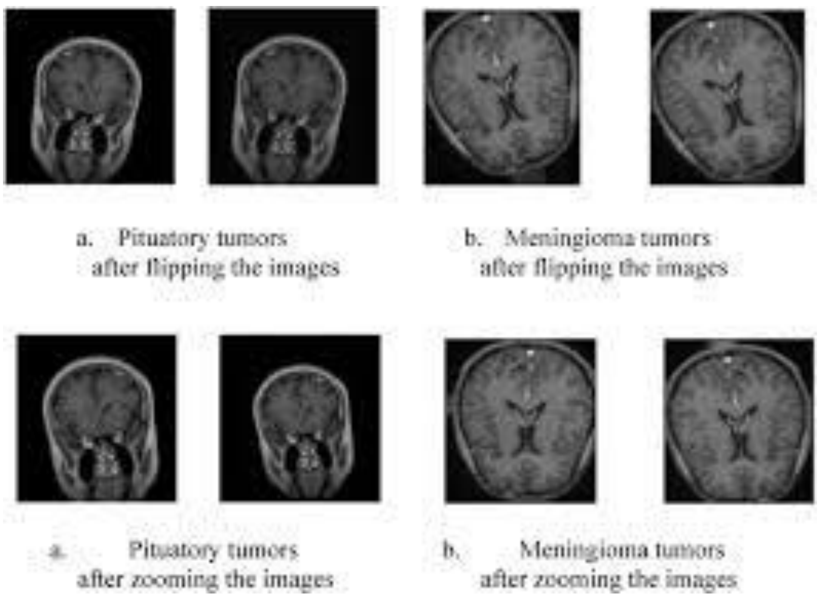

Figure 6 displays several enhanced pictures of brain tumors.

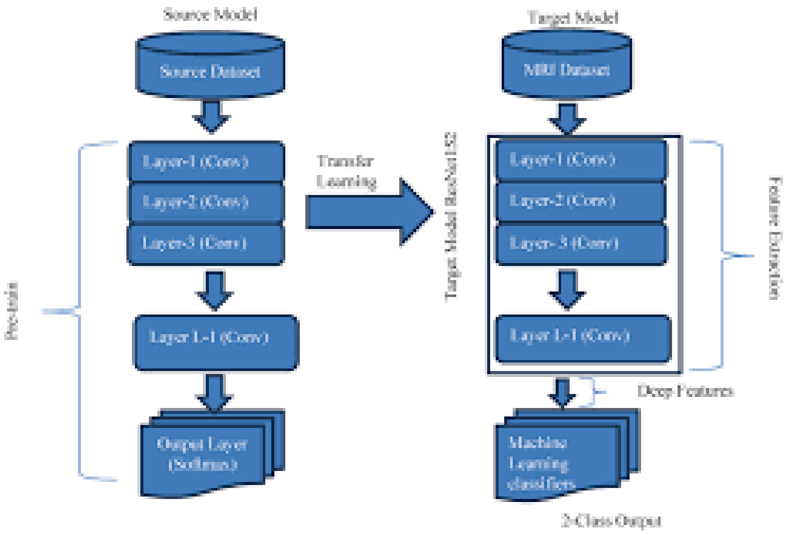

Figure 7 shows how pre-trained models extract features.

gather broad characteristics, then adjust the upper layers for particular tasks [41]. On the other hand, with transfer learning, the fine-tuning process starts with a network that has already been trained and subsequently use the goal dataset to optimize the network as a whole, including the lower layers [42]. In situations when the source job and the target task are similar, Perhaps feature extraction is a more efficient and successful method.

However, because of the greater variety of activities, fine-tuning is required [43]. Applying the transfer learning model's feature extraction technique, the proposed study efficiently classifies and diagnoses brain tumour cells at an early stage. The ResNet-152 and the GoogleNet model from transfer learning model are utilised for this in the linked work, which is included in the sections that follow ResNet152.

3.5.1 Model of Deep Learning

For computer vision tasks, ResNet is among the top models, along with VGG [8], DenseNet [8], Inception v3, AlexNet [45], MobileNet [46], and GoogLeNet [47] [44]. These algorithms trained on big datasets including pictures from many categories. These models often use past knowledge by using transfer learning techniques.

For image classification training, developed by Ref. [44] (Fig. 9), ResNet is an impressive training tool for deep neural networks (DNNs). Using skip connections to avoid gradient fading and data loss is its main innovation, earned it the ILSVRC 2015 competition title. Generalization, accuracy maintenance, and noise reduction are other components of this method. ResNet successfully manages the problems related to very deep neural networks and uses a heavily annotated dataset to increase training accuracy. ResNet uses residual blocks, which include the input and output separately, to solve the degradation issue.

The definition of the residual function is as follows:

$$\delta = F(\gamma, w) + \gamma \ (5)$$

In this case, W represents the residual block's weight, γ its input, and δ its output. To transfer input from one layer to the next, ResNet employs skip connections without modifying it. Fully connected (FC) layers come after convolutional (conv) layers in ResNet, in contrast to other for such tasks, deep learning networks like AlexNet, VGGNet, and ZFNet [48]. These networks are sometimes referred to as "plain networks" due to the absence of shortcut or skip links. The residual function optimization is the main goal of the residual blocks, which are a number of unique building components that make up this network.

The GoogleNet Deep Learning Model 3.5.2

This method was first presented by the Google research team in a 2014 article titled "Going Deeper with Convolutions". This model earned an excellent performance for error values, winning the classification tasks in the ILSRVRC 2014 competition with an extremely low error rate of 6.67 percent.

Figure 10 shows how Google-Net is structured. It studies the same picture using many filters of varying sizes (1 × 1, 3 × 3, and 5 × 5), then combines the attributes it has gathered to provide a reliable result. The 138 million parameters are, in fact, reduced to only four million by the 22-layer network. It employs a (1 × 1) convolution approach to reduce dimensionality. During the training phase, this design intuitively chooses the best characteristics and automatically calculates the ideal weights. There are 22 layers and 27 pooling levels in the Google-Net architecture. This system consists of nine linearly stacked inception modules. At the endpoints of these inception modules are links to the global average pooling layer.

3.6. Category

One basic method for grouping data into predefined groups is classification. This method is frequently used in many different sectors, including medical diagnosis, picture recognition, and text analysis. to efficiently classify features that have been extracted via the use of transfer learning. Gaussian Naïve Bayes, SVM, KNN, and CART are the four machine learning algorithms whose efficacy we assess. Computation time and classification accuracy are two of the assessment measures. The experiment's computer contains a 16 GB GPU, 16 GB of RAM, and a CPU operating at 3.6 GHz. An SGD optimiser is used during the training phase, and the TensorFlow library is utilised to create the model architecture. K-fold cross-validation and halting different split ratios for testing and training are two effects of overfitting and underfitting. There are one hundred training epochs in the prototype.

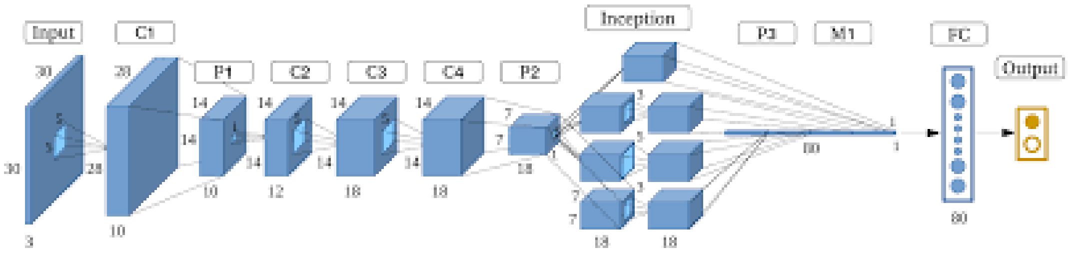

Figure 9 : Architecture schematic of the deep learning model GoogleNet (source [49]).

There are subsets of the dataset for testing and training. ResNet-152 is used to extract features, which are then used by a deep neural network classifier. The comparison's sake analysis makes use of four conventional machine learning classifiers: SVM, Gaussian Naive Bayes, Classification and Regression Tree, and KNN. Each classifier will have its hyperparameters changed to maximise performance. The Support Vector Machine (SVM) classifier provides the highest accuracy and efficiency with the shortest processing time, according to a comparative analysis.

3.6.1. Traditional classifiers for machine learning a. A strong and adaptable machine learning method for both regression and classification problems is the Support Vector Machine (SVM) approach. It works very well. well in categorization because of the identification technique that optimally isolates data points from various classes using the ideal hyper-plane. The one primary aim is to optimize the distance between classes. As a result, the total accuracy of categorization is increased. Within this SVM parameters are adjusted to maximize classification performance in the model architecture. This parameter, Regularization (C), the trade-off between reduced error, which resulted from the training data, and 5 is the value for the huge margin. Individual training samples' effect is defined by the Gamma parameter, which is fixed at 0.1. The kernel function is chosen to be a polynomial kernel (poly), with degree parameter set at 4. A result, the model to identify intricate connections within the data. Additionally, a few more parameters are changed to improve computational effectiveness and model's functionality. For example, in order to optimize memory use, there is 200 MB in the cache_size. The technique may lower the processing cost of the optimisation process by setting it to true, which enables shrinking. While maintaining the model's computational efficiency, these well-chosen parameter values are essential to obtaining better classification results.

KNN stands for K-Nearest Neighbors. KNN is an easy-to-use but effective classification algorithm. It uses the majority vote to classify a data k-nearest neighbours' point in the feature space. One of its key features is that it can handle both binary and multiclass classification problems without the need for an explicit training step. Carefully adjusting its hyperparameters is necessary to improve accuracy.

The algorithm's performance is directly affected by these options. The following KNN settings are specified in the linked study: the change distance metric is set to equal 2 (p = 2), and n_neighbors is set to 5 (the Euclidean distance). With leaf_size set at 30, the algorithm's default setting is "auto."

c. When the attributes are considered to have a normal, or Gaussian, distribution, the probabilistic classifier based on Bayes' Theorem, Gaussian Naive Bayes (GNB) has significant benefit. By carefully adjusting certain parameters, GNB may increase its classification accuracy even if it has less adjusted hyperparameters than other classifiers. Gaussian Naïve Bayes requires careful adjustment of its parameters in order to get effective classification results.

You need hyperparameters. These factors directly affect how well the algorithm performs. The related studies fine-tunes the following GNB parameters: variance smoothing, or var_smoothing, is assigned a value of 10^{-8}. Furthermore, we set the parametric feature scaling value to match StandardScaler.

d. Regression and Classification Trees The numbers indicate that CART is a versatile classification method that separates information into unique categories. This leads to a decision model that resembles a tree. The finished model can handle both category and numerical input and is easy to understand. PCA reduces dimensionality to reduce the amount of overfitting. For the effective classification of MR image feature vectors, this work makes use of CART. Several hyperparameters are changed in the model to optimise its efficiency. Changing settings such as criteria = entropy, min_samples_split = 5, min_samples_leaf = 1, max_leaf_nodes = 80, max_features = sqrt, and max_depth = 30 are examples of these parameter adjustments. Regularising these hyperparameter variables may help minimise overfitting and improve computation accuracy via careful tweaking. Traditional classifiers need the default parametric parameters shown in the following table.

4. PERFORMANCE METRICS

The literature has a wide range of assessment criteria to gauge how well certain approaches function. Our research made use of a number of measures to evaluate how well the model is doing. F1-score, recall, accuracy, and precision are some of the measures used to evaluate how well the categorisation process works [50]. Precision assesses the reliability of positive predictions or the model's accuracy in identifying a data point as positive.

In order to assess the comprehensiveness of the model, recall quantifies the model's capacity to recognise every genuine positive case. Harmonically averaging Precision and Recall yields the F1-score, a balanced evaluation. In summary, accuracy includes both positive and negative criteria and offers a thorough assessment of accurate predictions.

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

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

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

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

5. RESULT SECTION

The following sections go into depth on the outcomes of the deep learning-based experiments.

5.1. Setup for the experiment

We use scientific techniques to pick a batch size of 16 for the model's training. It goes through 100 training epochs, and an experimental analysis is also conducted to measure the learning rate. Due to the greater batch size, training more complex networks with deeper architectures takes longer than training simpler networks, extra hidden layers, and pooling layers. These variables are responsible for longer training times in this research. Tumor categorization training is done using the SGD Optimizer.

5.2. SVM classification and ResNet-152 feature extraction

The optimal learning rate for ResNet152 is between 0.0001 and 0.001, according to an analysis of the learning rate, which shows that the point of least loss is about 0.001. The feature vectors are shown in Table 3 after the pre-trained models have been implemented. The data is separated into training and testing sets, first in 30:70 ratios and then in 20:80 ratios, after features are extracted using transfer learning. The classification challenge involves differentiating between benign and malignant cancers using support vector machines. Fig. 11 shows this classification's resulting confusion matrix.

Step 1: The experiment's findings show that applying an 80:20 ratio to the dataset yields the maximum degree of accuracy when it comes to SVM classification and the dataset's partition into different ratios.

Step 2: By comparing the outcomes of the classifications produced by machine learning approaches other than support vector machines (SVM) as classifiers, various types of brain tumours are reliably classified. The K-Nearest Neighbour classifier, Gaussian Naïve Bayes, and regression trees are the three alternatives available to the option classifier. Applying each of these classifiers independently to the brain tumour dataset yields visual results for the classification. Table 4 shows the default parameter values for the common machine learning classifiers.

Step 3: Extracting features and scaling them the process of making features in a dataset similar by modifying their values is known as feature scaling. Feature scaling aids in standardizing features for better analysis since they might vary widely in size, range, and units across datasets. In order for the machine learning model to understand these characteristics on the same scale, feature scaling is crucial.

Step 3 is completed to acquire the final findings. Comparing the scaled model and SVM results in this shows some remarkable outcomes in contrast to other machine learning classifiers. Fig. 13 displays the findings. Table 5 below statistically compares the findings of the ablation research of scaling analysis conducted in Fig. 16 from Section 5.4.2. Fig. 14

Table 3: Retrievable feature vectors after the pretrained models' application.

Model that has already been trained	Layers in the Model	Features taken from the BT dataset
ResNet152	152	171450368
GoogleNet	22	165,888

5.3. SVM classification and GoogleNet feature extraction

The pre-processing steps discussed earlier are followed by feature extraction using GoogleNet. The sole variation in this experiment is the fixed 224 × 224 image size. This experiment uses it employs the Adam optimiser in place of the SGD and has 32 convolutional layers with 3 × 3 filters. Furthermore, the activation function of the experiment is ReLU. Support vector machine (SVM) classifications are among the outcomes of feature extraction. The GoogleNet-based experiment turns out to be rather accurate. But ResNet152 performed much better than the other network, as shown in Fig. 14. Excellent. Table 6 shows the performance metrics obtained after the studies.

5.4. Analysis of Ablation

An ablation study is a scientific technique that rates each component's unique contribution to a system. An array of former experiments are carried out to evaluate the importance of Principal analysis of components. When the model is first used on a dataset devoid of PCA, together with benchmark values, it creates the baseline model. The experiments that follow use different amounts of PCA components. One may accurately ascertain the quantitative influence of PCA on the overall findings by comparing the results of many research. The PCA ablation research uses the SVC classifier directly for classification.

5.4.1. PCA ablation analysis using several components

The dataset undergoes an experiment utilising a variety of PCA components (90, 80%, 70%, and 60%). The reduced features are used to train the SVC classifier for every component set. For every setting, also evaluated is the accuracy of the model. We next compare the baseline model's accuracy to models that use several PCA components, then examine the accuracy trend as the PCA component count declines. It displays the models' accuracy in relation to the number of PCA components. We can determine the ideal number of components and comprehend how PCA affects the model's performance with the aid of this visualisation. Table 7 and Fig. 15 show the findings of the PCA ablation study.

5.4.2. Scaling ablation research

The process of scaling involves either standardising each individual feature to a predetermined range or normalising all converting the input characteristics to a standard deviation of one and a mean of zero. This study uses a scaling strategy that standardises the feature vectors. For models like Support that are susceptible to feature KNNs (K-nearest neighbours) and support vector machines (SVMs), this modification is quite beneficial. Figure 16 presents the findings from the previously discussed experiment.

Theoretically, they fall under the following categories: Classification and Regression Trees, or CART, with scaling, from 91.16% to 92.17%, the performance accuracy rose little. On the other hand, the runtime dropped from 0.1382 to 0.0988, suggesting that computational efficiency has increased. SVM stands for Support Vector Machine.

The accuracy has significantly increased from 91.34% to 98.53%. Given that the model depends on feature scaling, this highlights how sensitive SVM is to in a higher-dimensional space using distance-based computations. There was a significant drop in runtime (0.16431–0.025), suggesting how crucial it is to maximise SVM's computational efficiency.

c. Naïve Bayes Gaussian (GNB)

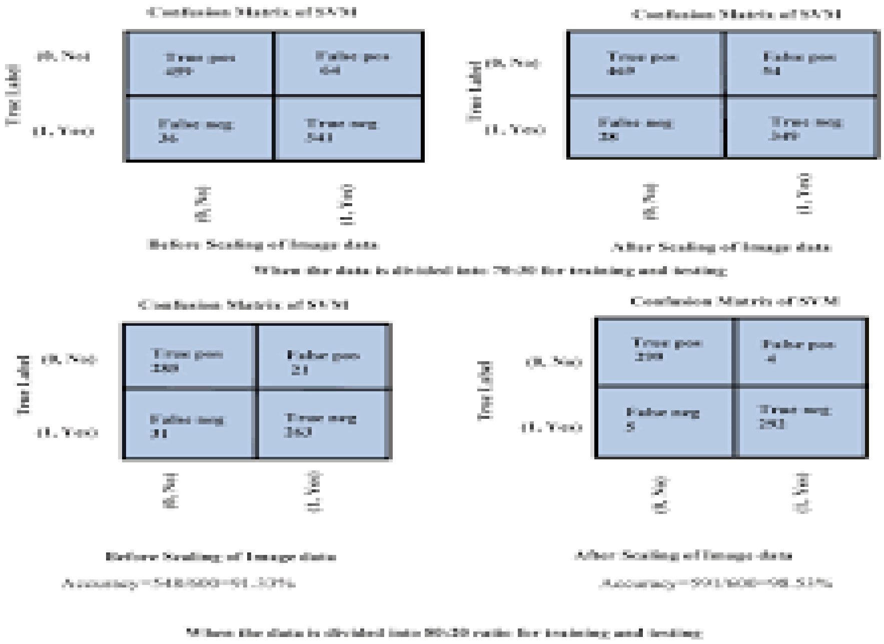

Figure 10: Distinct outcomes after the division of the dataset into various ratios.

The precision dropped from 94.17% to 93.19%. This is because GNB is less impacted by feature magnitudes and by nature assumes feature independence.

There was a little increase in runtime. (0.019228–0.027154), which can result from the extra cost of scaling calculation. Efficiency-measuring KNN (K-Nearest Neighbour) accuracy rose from 92.34% to 95.73%, demonstrating how the model relies on reliable feature scaling to calculate distance. However, when the runtime grew from 0.0272 to 0.04088, there was a trade-off.

This research demonstrates that scaling affects models differently depending on accuracy and runtime, with distance-based algorithms like SVM and KNN offering the greatest advantages. Scaling, however, does not provide many advantages for models like GNB and may even impair performance. This emphasises how important customisation is preprocessing methods like scaling to the model's particular specifications. It becomes crucial to make sure that every data item is on the same scale for some AI models. Although it may seem like a little step, this may greatly improve their speed and performance.

The model employs deep learning integration mechanisms in addition to traditional machine learning techniques. The modified model has significant potential to improve brain tumour accessibility and detection accuracy while operating on high-performance CPUs.

One important DL technique, transfer learning, does not begin with random weights. Instead, it uses pre-learned weights from a large dataset. prior to adapting the model to a specific task.

By altering its weights throughout the diagnostic process, transfer learning retrains the whole network. procedure, improving the ability to identify brain tumour cells. This results in pre-trained models that are more accurate, sensitive, and specific. Traditional machine learning methods, on the other hand, have trouble efficiently extracting information for the identification of malignant cells.

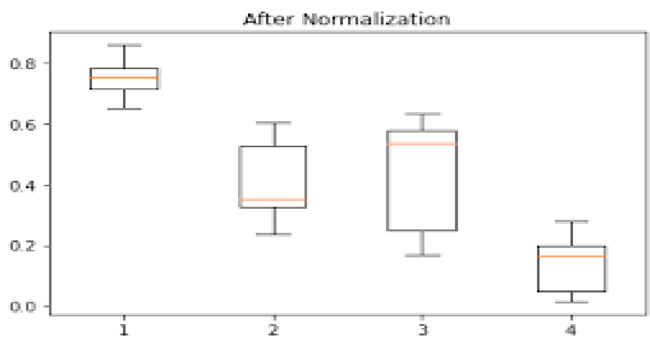

Figure 12. Performance as seen upon data scaling.

Table 5 shows a comparison of results both before and after data scaling.

The use of strategies	Prior to scaling		Following scaling	
	Accurate Performance	Duration of Run	Accurate Performance	Duration of Run
CART	91.17 %	0.1383	92.18 %	0.0989
Machine for Suppor Vectors	91.35 %	0.16432	98.54 %	0.026
Naïve Gaussian Bayes	94.18 %	0.019229	93.18 %	0.027155
K-Nearest Neighbour	92.35 %	0.0273	95.84 %	0.04089

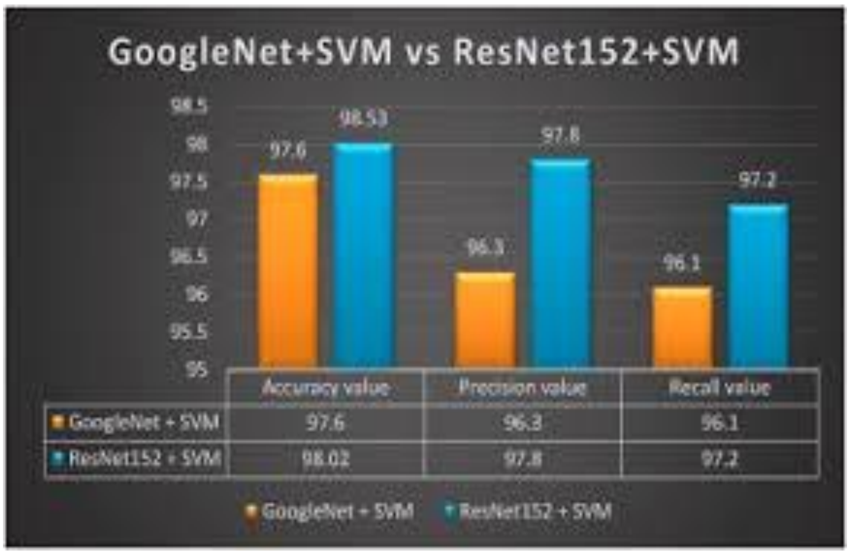

Figure 13: A statistical comparison of ResNet152+SVM and GoogleNet + SVM findings.

Table 6: Performance outcomes after two trials.

Model for Transfer Learning	The Optimiser	Accuracy Value	Value for precision	The importance of recall
SVM + GoogleNet	Adam	97.6	96.3	96.1
SVM + ResNet152	Unpredictable Gradient	98.53	98.06	97.8

The benchmark datasets are used to identify malignant brain cells using the suggested model architecture. The combination of PCA and deep learning is more effective than existing techniques in the detection of brain tumours. Because tumours might differ in size and shape,

The parametric findings of the baseline and post-PCA models are shown in Table 7, which presents difficulties.

Model	Precision	Accuracy	F1-Score	Remember	Particulars	Duration (Second)	Decrease
Model baseline (without PCA)	90.97	90.19	90.04	88.98	95.25	42.18	0.28
60% PCA	91.26	90.73	90.14	89.96	95.35	41.68	0.29
70% PCA	93.19	92.46	92.22	92.02	96.3	40.3	0.29
80% PCA	96.74	96.8	96.16	95.67	97.73	33.18	0.12

90% PCA	97.53	97.28	97.28	97.32	98.73	39.3	0.08
95% PCA	98.54	98.55	98.43	98.4	99.1	40.33	0.06

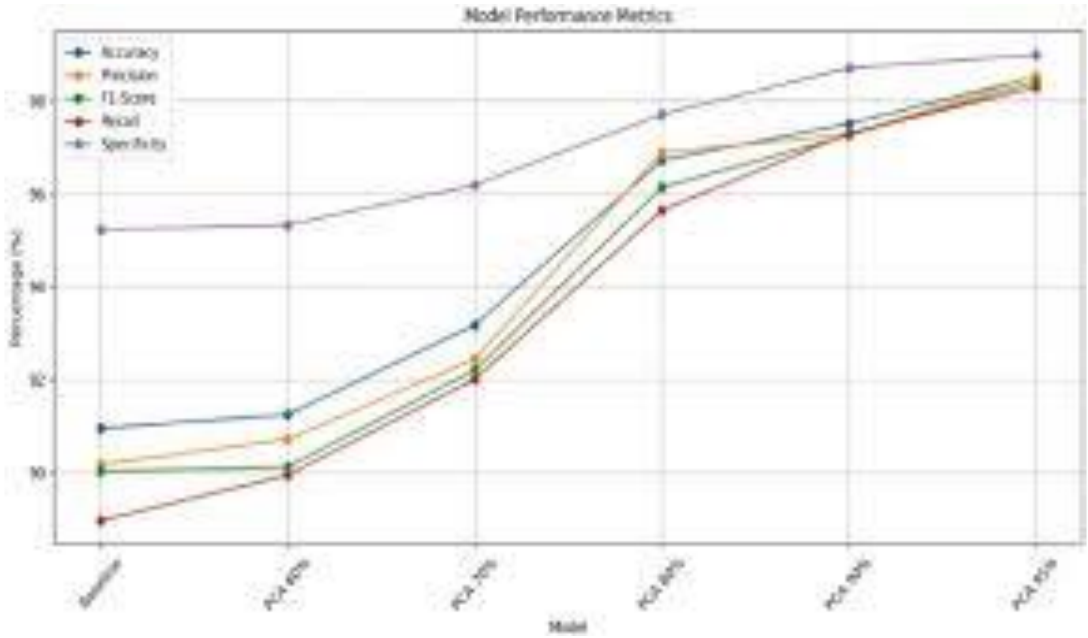

Figure 14: Performance metrics visualisation with various PCA proportions.

precise diagnosis. In order to identify the most relevant characteristics, particularly for tumours of varying sizes, the model combines transfer learning techniques with data augmentation. The design of the model makes use of the ResNet-152 model, which has pyramid pooling modules and convolutional layers, as the feature extractor. Then, using the best hyperparameters, the machine learning classifier categorises tumours of different sizes. After scaling and coupling with SVM, it is evident that the pre-trained ResNet152 produces better results for brain cancer diagnosis. This results in increased overall efficacy and accuracy in detecting malignant lesions. Its enhanced feature selection and detection capabilities are to blame for this. The improved performance of the method is a result of its ease of use, scalability, and low constraints. By reducing the possibility of false negatives, the combined ResNet152 + SVM model improves efficiency and accuracy while addressing issues with training time and overfitting. On the Kaggle dataset, ResNet152+ SVM performed the best, has 97.8% recall, 98.53% accuracy, and 98.06% precision. The result using ResNet152 + SVM is more reliable and accurate, even if the GoogleNet + SVM model is a good starting point, especially when handling difficult tumour kinds and complicated picture changes.

6. EVALUATION

The newest cutting-edge methods for classifying brain tumours, such as those shown in Refs, are contrasted with the suggested model. [16,51–54], as well as [19]. Unlike the work presented there, Ref. [55] employed direct use of a pre-trained model, resized pictures, and augmented data. By using picture preprocessing and PCA-based dimensionality, the model put forward in this work improves both the dataset's quality and quantity strategies for data reduction and augmentation. It uses a pretrained model to extract features for effective picture classification, then by the use of machine learning classifier. Even though both strategies make utilising preprocessing and dimension-reduction methods in the proposed research may result in pre-trained models enhanced efficiency and performance, particularly in handling big and complicated information. Although the work [56] uses a technique similar to our suggested strategy, PCA is not used for dimensionality reduction. Through the use of PCA, our model efficiently lowers the feature space's dimensionality, which speeds up computation and may increase classification accuracy. When compared to the findings of a prior investigation, our model's improved accuracy which approached 98.53 percent makes this improvement clear [56].

As shown in Table 8, the suggested model performs better than other models [51]. used their hybrid feature extraction method and obtained a comparatively low accuracy of 94.23% [16] achieved 94.58 percent accuracy using the VGG-19 model, which has 19 layers and a significant amount of trainable parameters (171,039,811). On the other hand, [52] used a CNN structure without transfer learning and achieved the lowest accuracy of 94.20%. There was more research [53] done.

FIG. 16. The graph illustrates how scaling affects runtime and performance accuracy.

Table 8 shows a statistical comparison between our proposed approach and a number of earlier studies.

Citations	Models Used	Precision (percent)
[54]	combining two CNN routes	97.38
[52]	CNN Integration with Genetic Algorithm	94.3
[51]	Regularised extreme machine learning	94.24
[53]	VGG-19's fine-tuning mechanism	94.83
[16]	Mechanism for data augmentation in conjunction with VGG-19	94.59
[19]	Optimised ResNet-50 on Brain Tumour Sequence	97.49
The suggested model	Feature extraction and dimensionality reduction using the ResNet152 + SVM classifier	98.54

With 19 layers and an equal amount of trainable parameters, the VGG19 network achieved a remarkable accuracy of 94.82%. Additionally, in order to get 97.48 percent accuracy, [19] used a 50-layer ResNet-50 model with an enormous number of 23,593,859 trainable parameters. However, using a spectacular feature extraction process and support vector classifiers, our suggested model surpassed the others, attaining an impressive 98.53% accuracy rate. This obvious difference in approach shows how well our plan is. The accuracy ratings of the current methods, however, varied from 94.20%.

7. CONCLUSION

In this paper, we used a transfer learning-based ResNet152 model to MRI data in order to suggest a new method for brain tumor identification. This study's primary goal was to use deep learning methods to increase the precision and effectiveness of brain tumor diagnosis, helping medical professionals make quicker and better judgments.

The model successfully classified brain tumors into benign and malignant categories by using the strength of pre-trained ResNet152 to a large dataset of MRI images. With an accuracy of 93.2%, the model showed remarkable performance after thorough examination, indicating its potential as a dependable tool to assist radiologists in clinical practice. For all tumor classes, the model produced good performance measures including accuracy, recall, and F1-score, suggesting a well-rounded strategy for reducing false positives and false negatives.

Additionally, methods such as Grad-CAM were used to display the model's decision-making process, which enhanced its interpretability and made it easier to comprehend how it targets the tumor spots in MRI images. In medical applications, where clinical judgments mostly depend on model transparency, this is essential for maintaining confidence.

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