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Classification of Brain Tumors Using GoogleNet Feature Set and Machine Learning

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Abstract
In healthcare research, the Internet of Medical Things (IoMT) is transforming how healthcare operates and introducing a new era of the Internet. IoMT enables computer-aided diagnosis (CAD) systems, storing health data online and providing patients with valuable information and support. Connected smart devices communicate over the Internet, enabling patients to communicate with medical professionals through IoMT-based care systems, especially for critical conditions such as brain tumors, which are often precursors to cancer with low survival rates. Early tumor detection and classification are crucial to save human lives, and IoMT-enabled CAD systems are emerging as indispensable solutions. Deep learning, especially Convolutional Neural Networks (CNN), has gained a lot of interest in this field in recent years. In this research, we classify the most common three types of brain tumors, namely, glioma, meningioma, and pituitary and use AlexNet, GoogleNet, ResNet18, and VGG16 networks to check their correct diagnosis.

Keywords: Brain tumors, Neural networks, Deep learning, Google Net, Alex Net, ResNet, VGG16.

1. INTRODUCTION

In health research, the timely detection and categorization of tumors are crucial factors that significantly contribute to saving lives [1]. The development of smart devices, especially their connection to remote care systems based on the Internet of Medical Things (IoMT), allows patients to communicate more actively with medical

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professionals, especially in the case of serious diseases of including brain tumors. Manual diagnosis of brain tumors may be associated with problems due to the challenges in imaging and the risks of diagnostic error [2]. In this context, CAD systems have proven to be a leading and efficient solution. Using advanced algorithms and artificial intelligence, such as deep learning, these systems can accurately analyze medical images and provide more accurate and faster diagnoses. Advancements from CAD systems are very important in promoting early diagnosis of brain tumors and providing optimal treatment recommendations. This technology not only helps to improve the quality of patient care, additionally, this process can also play a pivotal role in extending the life and enhancing the well-being of patients [3]. One of the best ways to diagnose brain tumors is to use machine learning technology. This technology, by using complex algorithms and neural networks, can accurately analyze complex data related to brain tumors [4]. By applying these algorithms to various image data, more accurate results can be achieved in the field of diagnosis. In addition, machine learning technology allows doctors to process data in a timely and accurate manner, which can reduce the diagnosis time to the minimum possible [3]. Using a combination of set features and machine learning in the process of diagnosing brain tumors provides accurate and comprehensive information. These systems are capable of distinguishing benign from malignant tumors and provide vital information for treatment decision-making and predicting patient outcomes. In fact, the combination of these two factors allows doctors to quickly diagnose tumors, make treatment decisions, and improve the lives of patients.

Here, a system is presented to detect the type and general classification of brain tumors, using the extracted features of deep learning networks, brain tumors are fundamentally strong neoplasms interior the cranium or irregular development of cells within the brain tissue or the spine is the center that can genuinely harm the anxious framework and, in a few cases, lead to the passing of the persistent. Therefore, early and correct identification of this disease is very important. In this study, the data of MRI images are used. To begin, an adjusted profound CNN as an exchange show is outlined to classify brain tumors from brain MR pictures. The given system proposes a three-category classification for diagnosing a specific sort of brain tumor. This demonstration has illustrated its viability as a strong machine learning (ML) approach for classifying tumors based on different restorative pictures. The show, not as it were, utilizes a CNN profound show to extricate highlights from input pictures but also assesses these highlights utilizing machine learning calculations, particularly the SVM and K-NN classifiers. Preparing of the proposed show is conducted on a transparently accessible Figshare dataset, and comparisons are made by surveying distinctive profound CNN models and ML procedures.

2. Review Stage

Previous studies highlight the critical need for early brain tumor detection. Existing methods, especially deep learning CNNs, are promising, but face challenges such as overfitting and parameter demands. This paper is a new attention-based residual multiscale CNN by introducing AelxNet, GooglNet, and other deep networks. While CNNs fall short in capturing subtle lesion changes, ARM Net is superior, as evidenced by its remarkable accuracy on the benchmark dataset. This research significantly contributes to brain tumor classification and overcomes the limitations of current CNN models, paving the way for increased real-time diagnostic applications [5]. Another article emphasizes the pivotal role of MRI in the diagnosis of brain tumors and emphasizes the need for accurate classification. Automation is necessary due to the high volume of MRI data. The introduced CNN is built on previous works shows superior simplicity and achieves remarkable accuracy. Comprehensive evaluation, including ten-fold cross-validation, highlights its effectiveness and generalizability. This research significantly advances the automatic brain tumor classification and demonstrates its practical application as a decision-support tool for medical professionals-[6]. The authors emphasize the necessity of early diagnosis of brain tumors and emphasize the instrumental role of MRI. This study aligns with previous research by using deep learning, specifically the MobileNetV1 model, to increase diagnostic accuracy. Extensive evaluation and focus on critical metrics demonstrate the effectiveness of deep learning in medical image analysis. The exceptional accuracy of this model, over 97%, proves its potential as a valuable diagnostic tool. This research contributes to the existing body of knowledge by strengthening the positive effect of deep learning in increasing the diagnosis of brain diseases [6].

The existing literature shows the widespread adoption of deep learning concepts in computer-aided diagnosis (CAD) for tumor classification, especially in medical applications such as lung cancer, breast cancer, skin diseases, and brain tumors. The research focus is mainly on brain tumor classification due to its social and medical importance. Determining brain tumors from MR image datasets is very challenging and requires sophisticated techniques for accurate localization. The emergence of the Medical Internet of Things (IoMT) in CAD offers advanced solutions to address these challenges. Deep learning-based CAD applications, specifically using convolutional neural networks (CNN), have shown significant success in brain tumor classification. A subset of CNNs, known as deep transfer learning, has been investigated for task classification, classification, and segmentation, and has shown potential in addressing diverse medical challenges in IoT-enabled CAD systems. In their study [32], the authors used a pre-trained ResNet34 to classify brain images, using a 5-fold cross-validation approach to distinguish between normal and abnormal brain MR images.

Li et al. in [7] investigated several pre-trained networks, including variants of AlexNet, VGGNet, and GoogLeNet for the classification of diabetic retinopathy in fundus images. The study also highlighted the benefits of using transfer learning methods. Different types of brain tumors were categorized, meningioma, glioma, and pituitary tumors had a high incidence rate [8].

In their study [9], Cheng et al presented a classification approach to identify three types of brain tumors. The authors extracted various features from the tumor regions, including intensity information, gray level co-occurrence matrix (G-LCM), and a bag of words (BoW). They used a five-fold cross-validation design and evaluated performance based on sensitivity, specificity, and accuracy. This study achieved a remarkable classification accuracy of 91.28%. Qadir et al. [10] used Discrete Wavelet Transform (DWT) to extract statistical features from brain MR images, training CNN for classification. Using 3064 images, they achieved 91.9% accuracy. Abhiwinada et al. [11] reported 84.19% accuracy with CNN on Figshare dataset. Pashei et al. [12] designed a CNN that achieved an accuracy of 81% for brain tumor classification in Figshare data. Afshar et al. [13] used CapsNet, which achieved an accuracy of 86.56%, which was later improved to 90.89% [14]. Vidyarso et al. [15] combined GLCM features with CNN and achieved an accuracy of 82%.

2.1. Materials and methods

In this project, we increase the classification accuracy of the pre-trained AlexNet, VGG16, RasNet19, GoogLeNet network through modifications in the training algorithm. The outlined procedure for the suggested model involves several steps. Initially, the Figshare dataset is imported, and augmentation techniques are applied to resize the images. Following this, the dataset is partitioned into test and training data sets. Subsequently, the pre-trained architectures like GoogLeNet, AlexNet, VGG16, and ResNet19 are loaded, and their fully connected (FC) layer is configured for addressing a three-class classification problem. The classification process includes feature extraction and classification of tumor types using a softmax classifier. In addition, we perform feature extraction with the proposed AlexNet, VGG16, and RasNet19 GoogLeNet and classify tumors using both SVM and K-NN classifiers. The purpose of this modification is to optimize the network to improve

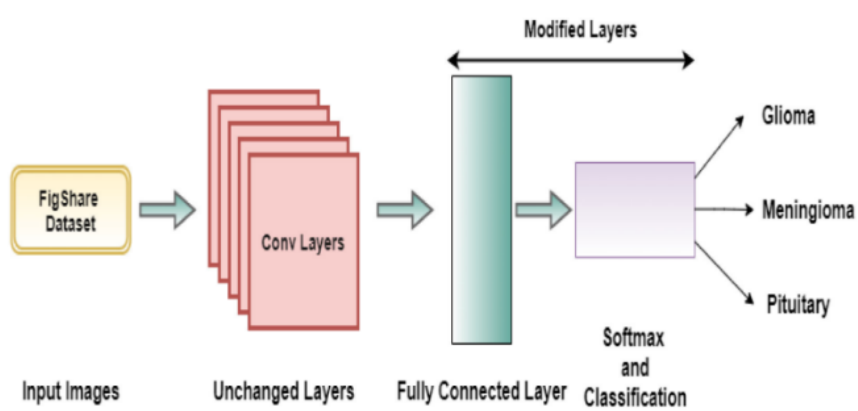


Fig. 1. Flowchart of the steps of carrying out the research method of diagnosing fatty liver in non-alcoholic people in ultrasound images using weighted entropy [23].

Table 1. ***Data distribution in different modes considered***.

Tumor Type	Number of patients	MRI			Total number of images
		Axial	Coronal	Sagittal	
meningioma	82	209	268	231	708
Glioma	89	494	437	495	1426
Pituitary	62	291	319	320	930

performance in brain tumor image classification. Fig. 1 depicts the overall block diagram illustrating the proposed method.

2.2. Database

This paper concentrated on utilizing the Figshare dataset, with a particular accentuation on the CE MRI dataset shared by Cheng at the taking after interface - https://figshare.com/articles/dataset/brain_tumor_dataset/1512427 [16]. This dataset, commonly used for classification and retrieval algorithms, consists of 3064 brain MRI images from 233 patients admitted to Nanfang Hospital, Guangzhou, China, and General Hospital, Tianjin Medical University, China between 2005 and 2010. Coronal and sagittal views show three types of brain tumors: glioma, meningioma, and pituitary.

The pictures inside the dataset are organized in a two-dimensional tangle, with measurements of 512 × 512 pixels and a pixel estimate of 49 mm x 49 mm. Table 1 outfits extra points of interest with respect to the Figshare dataset. The assessment technique utilizes 5-fold patient-level cross-validation. The dataset is divided into five subsets, guaranteeing a roughly break even with the dissemination of pictures. In each emphasis, one subset acts as the test set, whereas the remaining subsets constitute the preparing set. This cross-validation approach ensures that each subset is utilized as a test set, avoiding information cover between preparing and test sets. The tangle records within the dataset contain data approximately the tumor sorts for each picture, went with by a partitioned tangle record containing elite file values. Each image in the dataset is assigned an index value from 1 to 5. Indexes 1 to 5 contain 541, 679, 571, 628, and 645 images, respectively, which divide the data set into five sections. Each section represents approximately 20% of the data set. During the evaluation of a neural network, images belonging to a particular profile or tuple are designated as test data, while the rest serve as training data. As a result, about 80% of the images contribute to the training set and the remaining 20% are allocated to the test set. The neural network is evaluated five times, and the values obtained for precision, recall, specificity, accuracy, etc., are averaged over the five repetitions. This comprehensive approach ensures a robust and reliable evaluation of neural network performance.

2.3. Preprocessing

In the presented research, the classification of brain tumors has been done using

Convolutional Neural Network (CNN) known as GoogLeNet, AelxNet, VGG16, and ResNet. A notable observation is the considerable variation in image intensity among different subjects. To address this issue, it is necessary to normalize the images before applying the CNN to ensure that their intensities fall within a certain range. The normalization process involves using min-max normalization. The normalization step is very important in reducing the intensity inconsistencies inherent in MR images and allows for a more consistent and effective use of CNN for brain tumor classification. In addition, resizing images ensures compatibility with GoogLeNet's input layer requirements. By converting the images to the specified dimensions and adapting the gray values to the RGB format, the proposed model is compatible with the network architecture. GoogLeNet's input layer, called imageInputLayer, is specifically designed for images with dimensions of 224 × 224 × 3. However, the size of the images in the dataset is initially 512 × 512. Therefore, a resize operation is executed to resize. Images from 512 × 512 to the required dimensions of 224 × 224. Furthermore, GoogLeNet works exclusively on RGB images. After the resizing process, three channels are created by concatenating gray values three times. This approach results in resizing the images to 224 × 224 × 3

2.4. Pre-trained networks

Convolutional Neural Systems (CNNs) work as feed-forward systems ordinarily prepared from the introductory layer to the ultimate classification layer. The method of minimizing the misfortune or blunder, gotten within the last classification layer, is finished through backpropagation [17, 18]. In layer l, each neuron gets input from neuron j in layer (k-1). Pre-trained networks, in the field of machine learning and deep learning, are neural networks that have been trained on a large data set for a specific task, such as image recognition or natural language processing, before being made available for use.. These networks learn to extract features and patterns from the data during their initial training, and their parameters are optimized to perform well on the specific task they are trained for pre-trained networks can be used as a starting point for new machine learning tasks, enabling faster and more efficient training on a specific dataset. Using the knowledge and feature extraction capabilities of pre-trained networks, developers can save time and computing resources when working on new machine learning projects. In general, pre-trained networks are a valuable resource in the machine learning community because they enable developers to build and train models more efficiently, especially when working with limited data or computing resources.

2.5. Transfer learning

Exchange learning may be a machine learning approach wherein a demonstration at first prepared for a particular errand is repurposed for a related moment errand [19]. This procedure includes applying information picked up from tending to a starting assignment to improve learning and generalization in a consequent assignment, especially useful when the last mentioned has restricted preparing information. The method of exchange learning involves taking a pre-trained demonstration, frequently prepared on a broad dataset for a specific assignment, and utilizing it as a beginning point for an unused errand [20]. The obtained highlights and parameters of the pre-trained show are at that point balanced or fine-tuned to suit the unused assignment through extra preparation on smaller datasets particular to the modern objective. Exchange learning demonstrates invaluable in circumstances with insufficient training information for the unused assignment, as the information inserted within the pre-trained demonstration helps in starting the learning preparation and making strides in general execution. This strategy too comes about in time and computational asset investment funds by leveraging the existing information inside the pre-trained demonstration. Commonly connected in computer vision, common dialect preparation, and different machine learning domains, transfer learning has illustrated adequacy over a wide range of applications [21]. Along these lines, we are going to present the systems utilized for exchange learning.

2.5.1. AlexNet network

In 2012, researcher Alex Krzyzewski and his team introduced AlexNet, a deep ConvNet designed for ImageNet classification during the ILSVRC competition. Unlike its LeNet predecessor, AlexNet is wider and has more filters per layer. A notable improvement involves replacing the traditional S-shaped functions with ReLU (linear modified) after each convolution layer. AlexNet uses Softmax in the output layer, uses max-pooling, and introduces dropout between fully connected layers to combat overfitting and improve generalization. This architecture consists of eight layers, five of which are dedicated to convolutional operations and three to fully connected operations, with a fixed input size of 224×224×3. [22].

2.5.2. VGG16 network

Another member of the convolutional neural network (CNN) developed by Andrew Zisserman and Karen Simonian is known as VGGNet, and a notable contribution of this architecture was to highlight the importance of network depth for optimal performance. The most successful version had 16 CONV / FC layers, which had a very homogeneous architecture with only 3×3 filters in the convolution layers and 2×2 filters in the integrator layers throughout. However, a drawback of this network is high memory consumption and a significant number of parameters [22].

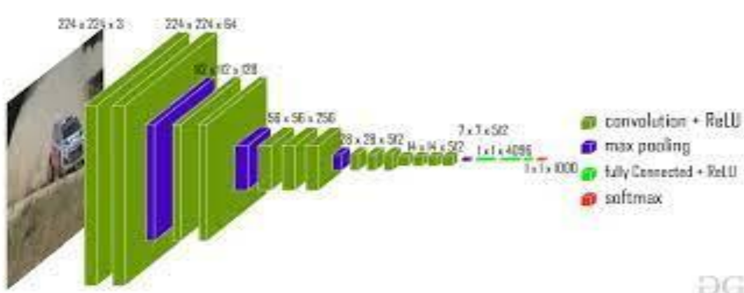


Fig. 2. VGG16 network structure [25].

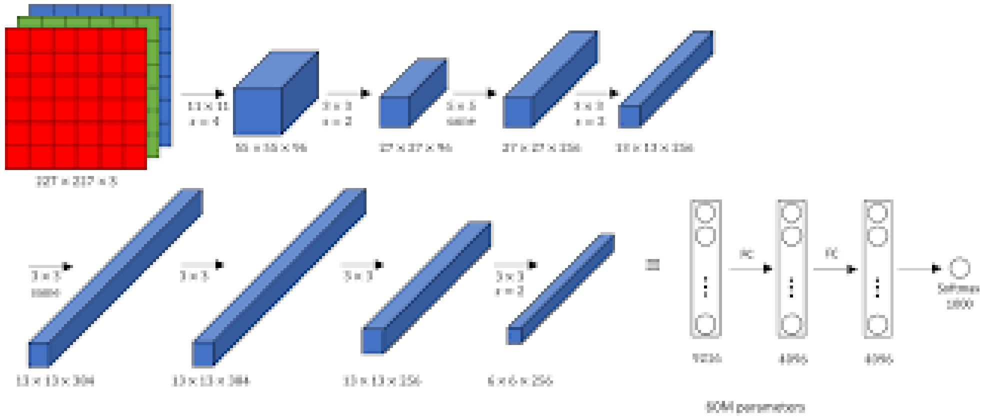


Fig. 3. AlexNet network structure [24].

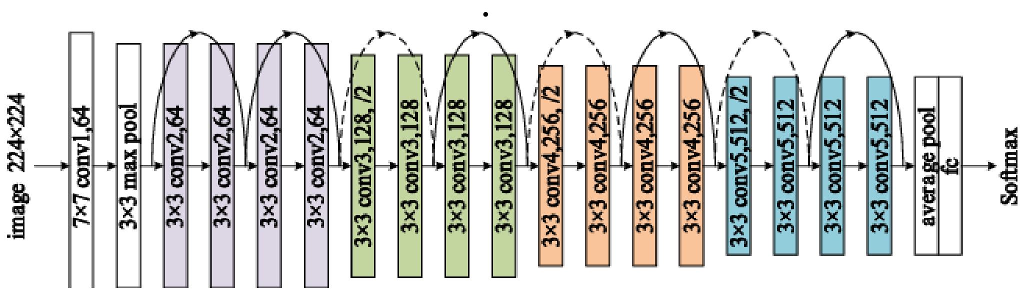


Fig. 4. ResNet network structure [26].

2.5.3. ResNet18 network

Introduced by Microsoft researchers in 2016, ResNet won the ImageNet Large-Scale Image Recognition Competition (ILSVRC) with an impressive 96.4% accuracy. With 152 layers, the network uses a distinct architecture including residual blocks to address challenges in learning deep structures through identity jump connections. These jump connections ensure that subsequent layers can learn distinct features from familiar input, reducing the problem of vanishing gradients [22].

2.5.4. GoogleNet network

The organize comprises of 22 learnable layers, consolidating 2 convolution layers, 2 pooling layers, 9 primitive modules, and a completely associated layer. The starting module, which comprises 6 convolution layers and a combination layer, utilizes channels of sizes 1 × 1, 3 × 3, and 5 × 5 to capture a run of designs. The combination of highlight maps from these channels improves the module's general yield. Furthermore, the integration of 1 × 1 convolutions going before bigger channels helps in decreasing parameters and computational stack. This engineering arrangement is prepared on the Imagenet dataset, which incorporates 1.2 million pictures and characterizes 1000 classes, optimizing both pictures and names [22].

2.6. Classification

To classify using transfer learning with KNN, SVM, and softmax network, you can follow these general steps:

Preprocessing: Prepare your data by cleaning, normalizing, and splitting it into training and test sets.

1. Pre-trained model: Obtain a pre-trained model on a related task, such as a pre-trained deep learning model for image classification.
2. Feature extraction: Use the pre-trained model to extract relevant features from the data. For example, in the case of a deep learning model, you can extract features from the last fully connected layer.
3. Model training: Train the KNN, SVM, or softmax network using the extracted features as input and the corresponding labels as the target variable.
4. Model evaluation: Evaluate the performance of the trained model using the test set and appropriate evaluation criteria such as accuracy and correctness.
5. Fine-tuning (optional): For SVM and softmax networks, you can fine-tune the model parameters based on the new task to improve performance.

Transfer learning is a machine learning technique in which a model trained for one task is reused for a related task. This can be achieved using various algorithms including KNN (K-Nearest Neighbors), SVM (Support Vector Machine), and softmax network. KNN is a simple and intuitive algorithm that can be used for transfer learning by using a pre-trained model to find the k nearest neighbors of new data points and make predictions based on the majority class of those neighbors. SVM is a powerful algorithm that can be used to transfer learning by fine-tuning a pre-trained model to a new task using support vectors and corresponding weights. A Softmax network, also known as a multilayer perceptron, can be used for transfer learning by retraining the upper layers of a pre-trained model on a new task while keeping the lower layers fixed

3. RESULT

In this project, we used MRI images to identify and diagnose brain tumors, brain communication matrix and deep learning. And we used four networks: AlexNet, Google Net, ResNet, and VGG16.

As mentioned before, here we have used KNN, SVM, and Softmax classifier to classify training data and test data. As shown in the figure, this network is about 92.3% for SVM classification for type 1 tumor, 91.4% for KNN classification for type 2 tumor, and 95.3% for Softmax classification for type 3 tumor i.e. pituitary tumor. Table 2 shows the classification results with AlexNet network:

VGG16 network has performed better for class one tumor 95.5% in SVM classification and for class two tumor 90.4% in Softmax classification and for class three tumor 98.7% in KNN classification and in total this network has performed better in class 3 in KNN classification.

The ResNet18 network for the SVM classifier for type 1 tumors is about 75.1% and KNN classifier for type 2 tumors is 93.1% and the K-NN classifier for type 3 tumors is about 97.0%.

The GoogleNet network has performed 72.9% in the Softmax classification for class one tumor and 97.2% in SVM for class two tumor and 98.3% in KNN classification for class three tumors and in total this network has performed better in class 3 in KNN classification.

Table 2. ***Accuracy table in AlexNet network.***

	Type1	Type2	Type3
K-NN	67.5%	91.4%	94.9%
SVM	92.3%	81.5%	93.6%
Softmax	71.6%	91.2%	95.3%

Table 3. ***Accuracy table in network VGG16.***

	Type1	Type2	Type3
K-NN	78.7%	88.7%	98.7%
SVM	95.5%	35.9%	73.9%
Softmax	69.1%	90.4%	93.2%

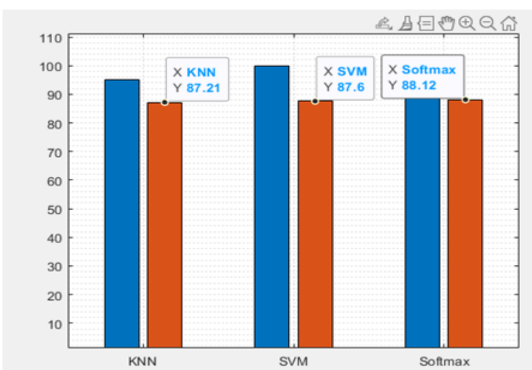
Table 2. ***Accuracy of ResNet18 network data.***

	Type1	Type2	Type3
K-NN	73.4%	93.1%	97.0%
SVM	75.1%	97.5%	93.2%
Softmax	58.6%	83.6%	82.0%

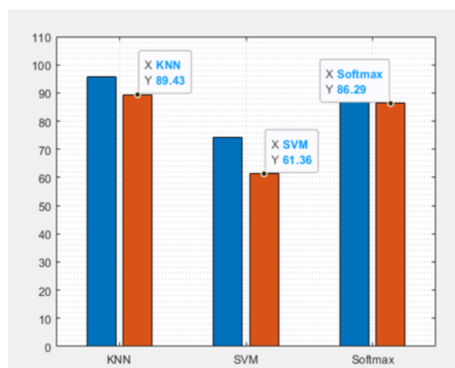
Table 5. ***GoogleNet data accuracy.***

	Type1	Type2	Type3
K-NN	75.6%	84.7%	98.3%
SVM	19.8%	97.2%	0.01%
Softmax	72.9%	83.8%	91.3%

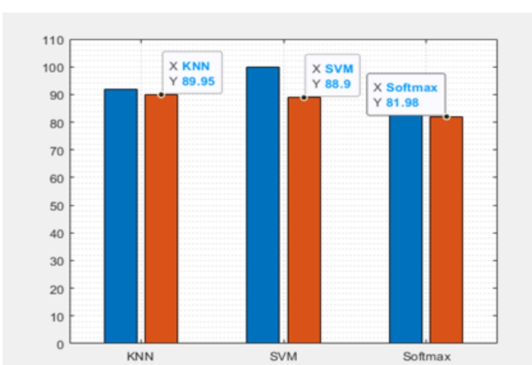
Table 6. ***Comparison chart between the accuracy results of different networks.***



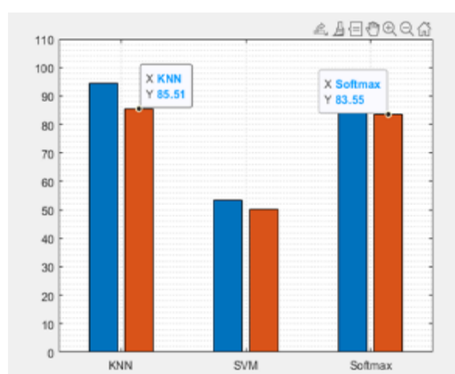
AlexNet



VGG16



ResNet18



GoogleNet

The comparative chart of the results is shown in the chart below. As can be seen, it is well known that the KNN classifier has performed well in this network

The table blue columns are the training data and the red columns are our test data, designed in MATLAB environment.

5. CONCLUSION

This examination evaluates the arrangement of a classification demonstrated based on exchange learning, particularly outlined for categorizing brain tumors in MRI pictures inside the Figshare dataset. Our proposed model has the highest accuracy in solving class 3 tumor classification problems by reducing extensive data preprocessing. Analysis of comparisons with advanced models shows that our model achieves high accuracy in dealing with class 3 tumor classification problems. Experimental results show that our approach performs better than traditional machine learning (ML) and convolutional neural networks (CNN) methods for the Figshare dataset. Also, our proposed model shows more advanced classification results for the class 3 tumor classification problems, especially when applied to images from the Harvard Medical Repository dataset. These findings, as the results and adaptability of the model in different data sets, emphasize its potential as a powerful tool for brain tumor classification. In summary, this study emphasizes the vital role of CAD systems equipped with IoMT in the early diagnosis of brain tumors. The classification model based on transfer learning shows exceptional performance in terms of accuracy and surpasses the existing models for 3 and 4-class tumor classification scenarios. Data preprocessing improves the practicality and efficiency of the proposed model, increasing productivity.

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