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The use of artificial intelligence-supported communication technologies in neurological fields: A case study on brain tumor detection

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ABSTRACT

Objective: The global health system is being shaped by multidisciplinary studies on the diagnosis of diseases and the provision of effective treatment services. Information and communication technologies have been developing laboratory and imaging studies through artificial intelligence-supported systems for the last twenty years. Studies with high accuracy levels in the diagnosis and treatment protocols of diseases make important contributions to making healthy decisions. Artificial intelligence applications have been actively used in the treatment processes of neurological cancer cases in the field of health, as in many fields in recent years. Among these applications, the machine learning model has started to be preferred in the detection of brain tumors because it can provide remarkable results. The main purpose of the study is to provide a supportive analysis for the organization of early diagnosis and rapid treatment in areas such as intracranial pressure, tumor treatment and radiotherapy of patients during intensive care processes.

Materials and Methods: In this study, the method developed by doctors with machine learning Kaggle and developers of samples in the network through an example of an application that was developed through machine learning on brain tumors, brain tumor detection carried on with the validation of the data sets includes four classifications.

Results: The study consists of two different study systems, namely practice and test. Sectional images from 2865 brain magnetic resonance imaging (MRI)and computed tomography (CT) samples were examined as training in the first stage of the application using the convolutional neural network (CNN) model, and the detected tumors were classified. In this context, MRI results were obtained on 2865 samples with 2470 units and 86.23% with tumors, and 395 units and 13.76% no tumors.

Conclusion: In the study, samples with tumors were detected in a 3-month period for brain tumor detection with artificial intelligence and classified typologically. Accordingly, the reliability of the application was proven by providing 98.55% verification on 2865 samples, 3 different tumor types and no tumor data.

Keywords: Tumor detection, MRI, Artificial intelligence, Kaggle, Case study

1. INTRODUCTION

In the 21st century, in which information and communication technologies spread rapidly, there is a tendency to artificial intelligence applications in the treatment processes in the field of health, as in many other disciplines. The use of artificial intelligence in health has started to be used in neurological fields in recent years to reduce the error rate of early diagnosis and treatments. It is seen that the global health system is turning to artificial intelligence solutions for the detection of neurological-based tumors with tools such as deep learning and machine learning to combat complex and difficult data.

Brain tumors turn into possible cancer cases if subjective decisions are made in the pathological and clinical processes of the central nervous system as the activities of the neoplasm group, apart from the surrounding tissues. In the face of the development of brain tumors through mutations and gene fusions, magnetic resonance (MR) and computed tomography (CT) solutions are performed, apart from molecular tests.

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On the other hand, models with a relatively superior level of objective decision, such as artificial intelligence, are preferred for the detection and classification of brain tumors.

Cancerous structures in brain tumors are divided into benign and malignant tumor groups. Benign tumors may not cause harm to the patient's health because they do not carry cancerous cell characteristics. On the contrary, malignant tumors, on the other hand, as cancerous structures, can also spread rapidly to other tissues in the brain. Human being is physiologically directly proportional to the way cells regenerate. When aging and damaged cells turn into malignant tumors in the face of regeneration, this regeneration process is prevented and can cause the production of tumor tissue cells in the process.

Regarding brain tumors, the risk of brain cancer has been increasing on all individuals in recent years. Because it is determined that there has been a rapid increase in this issue at the level of 30% in the last 300 years. Brain tumors can basically be seen in two different ways. It can occur when the tumor grows in intrabrain cells on tissue or spreads from primary areas to the brain, which is observed in other organs [1]. Important research has been carried out in recent years on the study of brain tumors and cancer. This type of cancer has a structure that also limits the ability of other organs to function, which occurs when cells grow uncontrollably [2-4]. Here, within the general structure of the masses; these growths take place on cells such as glial cells, neurons, lymphatic tissue and blood [5]. There are different types of brain tumors. Among them, glioma, medulloblastoma, lymphoma, meningioma, craniopharyngioma, pituitary decubitus come to the fore in particular [6].

Brain tissue and tumor segmentation are being determined through magnetic resonance imaging (MRI) and CT images, which are one of the most applied areas in brain tumor detection in recent years [1,7,8]. One of the various algorithms and sample study areas developed for the detection of brain tumor is seen as MRI. MRI is the most widely used imaging technique in radiology to visually visualize human structure and function. The issue of presenting MRI images with a low margin of error also shapes an important field of study in the field of classification in the field of medicine. Vankdothu and Hameed [9] and Damodharan and Raghavan [10] in their study classify the general characteristics of pathological tissues as well as other segments by proposing a brain tumor detection technique through an alternative cluster and segmentation study for MRI applications.

Various algorithms have been developed for brain tumor classification. Within these algorithms, K-Mean Clustering includes numerical, unsupervised, non-deterministic iterations. Here, while there is at least one element in the clusters, each element is positioned near the center of its cluster [6].

Layered structures are shown as an important justification for providing an orientation to artificial intelligence in the field of brain tumor classification. The fields of artificial intelligence and application forms (such as machine learning and deep learning) have multi-layered structures. Because neural networks located between input and output generally consist of a two-Decker structure. This can also ensure that the percentage of validation on the taught data is increased when different layer and node sales are increased. At this point, different parameters and calculation resources can also be used.

The main purpose of using Graphics Processing Units (GPU)s in machine learning and deep learning applications, particularly in the field of artificial intelligence, is to enhance the performance and accuracy of data analysis, especially in MRI calculations. GPUs play a crucial role in achieving detailed learning principles that involve data labeling with algorithms. Their primary purpose is to act as the deciding factor in data analysis, particularly in critical domains such as health and engineering, where accurate and reliable results are essential for preserving lives and ensuring optimal outcomes. By leveraging GPUs, complex data classifications can be performed efficiently, enabling the processing of large amounts of data through high-scale matrix calculations. This ultimately leads to more qualified and precise results in the field of MRI calculations and other related areas.

2. MATERIALS and METHODS

Previous Studies

It is considered as an effective technique in the recognition of a brain tumor, identification of treatment processes and recovery processes. The brain tumor is experiencing different formation, development and change processes from each other. Volume structures, cross-sectional values and imaging techniques for processing images and image fragments constitute the required data area. In 2009, Sharma developed a new brain tumor segmentation in 2D and 3D and created a computational model that will determine the overall area and volume of the tumor using data sets for surgical planning [11].

On the basis of the imaging performed via the MRI device, the water molecules present in the human tissue, the hydrogen nuclei are spatially encoded and the image is obtained by providing a signal [12,13]. Detecting the tumor region using MRI alone is not enough, and radiologists in particular are trying to achieve diagnostic accuracy with new technological systems such as machine learning in order to determine treatment by measuring the size of the tumor region [4]. In another study, Gopal and Karnan classify groups with and without brain tumors using image processing algorithms on 42 MRI samples. This classification has reached an accuracy rate of 92% with the particle swarm optimization technique [14].

Machine learning represents an important field of study in tumor detection and classification processes. Al-Dahshan and the others et al., emphasizes that within the general field of machine learning there are actions of preprocessing, dimensionality reduction, feature extraction and object selection [15]. The subject of deep learning is one of the important areas of artificial intelligence used in the detection of brain tumors in recent years. Deep learning is an artificial intelligence model that constitutes a subset of machine learning that uses a hierarchical structure based on representative learning. On the basis of the increase in studies carried out through deep learning in tumor detection, it is effective that GPU can perform calculations on a lot of data without human intervention, since they are in the structure of automation and analytical analysis.

Mohsen et al., conducted on the classification of brain tumors., in a sample study conducted by, normal, glioblastoma, sarcoma and metastatic bronchogenic carcinoma tumors were detected by performing 4 classifications via deep neural networks on 66 brain MRI [16]. MRI samples are often preferred for brain tumor and imaging processes. In these imaging models, various experimental studies can be carried out in order for brain tumor lesions and volumes to move to a stationary level in 2D and 3D. Evaluation of brain tumors through two different application modules as training and testing positively shapes the verification and reliability processes of research.

In addition to research on classification and detection of brain tumor methods, the conversion of analysis times of tests into output is also considered to be another important detail. Dahab et al., the level of the result times of the tests were examined within the scope of the study in which they made two different suggestions by [17,18]. In this study, firstly, based on an integrated set of image processing algorithms, and secondly, based on the structure of probabilistic artificial neural networks developed and implemented via Matlab. MRI images were selected as a test set out of 18 randomly selected samples out of 64 subjects by simulation, while 46 subjects were used for training. It was found that the processing time was shortened by 79% during the measurement process with the Learning Vector Quantization (LVQ)-based probability neural network (PNN) system. Tun Zav et al., based on a Naive Bayesian classification model based on a class and category based on an important taught data set for the detection of brain tumors., in a sample study conducted by 50 MRI images, structures with tumors were examined at a rate of 81.25%, structures without tumors at a rate of 100%, and a verification level of 94% was achieved [19].

While important application methods for brain tumor and artificial intelligence are considered as machine learning and deep learning, models that provide detection, such as the Convolutional Neural Network (CNN) model, can make important contributions in this process. It is also accepted as a recommendation study in clinical studies as a sample study that determines segments by performing tumor detection via CNN with 92.13% accuracy and 7.87% margin of error [18].

Tumor Detection and CNN Model

Among the models used for the detection of brain tumors, there is also CNN method. CNN is a machine learning model from the type of artificial neural networks [20]. In this model, it performs tasks such as classifying, recognizing or predicting data by learning based on input data. CNN's work especially effectively in problems related to images and manage to learn the properties of images.

The detection of brain tumors is a problem with images, which is why a model such as CNN can be used. In particular, CNN can be used for the detection of tumors using MRI of the brain. These images are taken by taking advantage of the magnetic properties of the brain tissue and show the areas where tumors are located [20-23].

The CNN model takes brain MRI images as input and tries to detect whether there are tumors or not. This model can be pre-trained or trained. A pre-trained model can give better results when applied to an unprecedented set of data. However, if the model has not been trained in advance, the model can become more effective for the detection of tumors by learning by training.

In the training process, data sets are used that are known whether the brain MRI images given as input to the model contain tumors. The model is trained by selecting samples from these data sets. During the training, the teaching model learns the features of MRI images and tries to detect the presence of tumors. After the completion of the model training, the model brain can be used for the detection of tumors when applied to MRI images. The model processes the brain MRI images given as input and tries to detect whether there are tumors or not. This detection result is given by the model as a result output. This result can be a dialog box or a number indicating the presence of a tumor.

However, the use of the CNN model for the detection of tumors also brings some disadvantages. For example, the performance of the model may decrease if there is not enough dataset for the training of the model. In addition, the use of the model for the detection of tumors may not fully adapt to the clinical evaluation process and decision-making process of doctors. Therefore, in addition to the use of the CNN model for the detection of tumors, the clinical evaluation process and decision-making process of doctors are also taken into account [24,25]. CNN architecture is generally accepted as a classification, object identification and detection method [26].

The use of the CNN model for the detection of tumors makes it possible to learn the features of brain MRI images. Thanks to this, the model tries to detect the presence of tumors. However, the use of the model for the detection of tumors also entails some disadvantages. For example, the performance of the model may decrease if there is not enough data set for the training of the model. In addition, the use of the model for the detection of tumors may not fully adapt to the clinical evaluation process and decision-making process of doctors. Therefore, in addition to the use of the CNN model for the detection of tumors, the clinical evaluation process and decision-making process of doctors should also be taken into account.

In addition to using the CNN model for the detection of tumors, other machine learning models can also be used. For example, the support vector machine (SVM), a model that is able to learn the characteristics of brain MRI images, can also be used. SVM performs classification by parsing data on a special plane and performs tasks such as classifying, recognizing or predicting data by learning based on input data [27]. In the studies conducted based on the CNN model, Swati et al., conducted a method study to analyze MRI images using a pre-trained CNN model. In this study, five additives provided a level of 94.82% with a verification feature [28]. In the study developed from SR-FCM-CNN models based on Fuzzy C-Means model, and in the study conducted on 500 samples selected from the Cancer Imaging Archive, a verification level of 98.33% was achieved through MRI images [29].

Convolutional Neural Network and other machine learning models can be used for the detection of brain tumors. However, it is important that there is enough data set for the training of the model and that the model adapts to the clinical evaluation process and decision-making process of doctors. Therefore, the models used for the detection of brain tumors should be carefully evaluated by doctors.

Methodology

In this study, a two-stage software and application process was determined for the brain tumor classification process. The brain tumor detection software analysis installation usually consists of two main components, an imaging system and a data analysis software. These two components are integrated with each other and used for scanning brain images, detecting tumors and evaluating the characteristics of tumors. Within the scope of the research, an artificial intelligence scheme was determined through the CNN model via the Kaggle data set in the tensorlow library via the python software language and machine learning was performed.

In this context, the installation of the imaging system and the installation of the data analysis software have been provided for the installation. Below is a general installation scheme for these two components:

Installation of the imaging system: this system is usually used to scan images of the brain magnetic resonance imaging (MRI) or computed tomography (CT) imaging techniques, such as with one of works. This system requires a scanning device for scanning brain images and a data processing server for processing scan data. The scanning device generates magnetic field or radiation waves that are used to scan brain images. The data processing server, on the other hand, processes the data generated by the scanning device and creates images.

Installation of data analysis software: This software is used to detect tumors and evaluate their characteristics after scanning brain images. This software can be an application running on a data processing server, or it can be run on a computer. The data analysis software examines the images generated after scanning the brain images and uses a series of algorithms to detect tumors. These algorithms can perform operations such as detecting tumors according to the characteristics of tumors, determining the size and location of tumors.

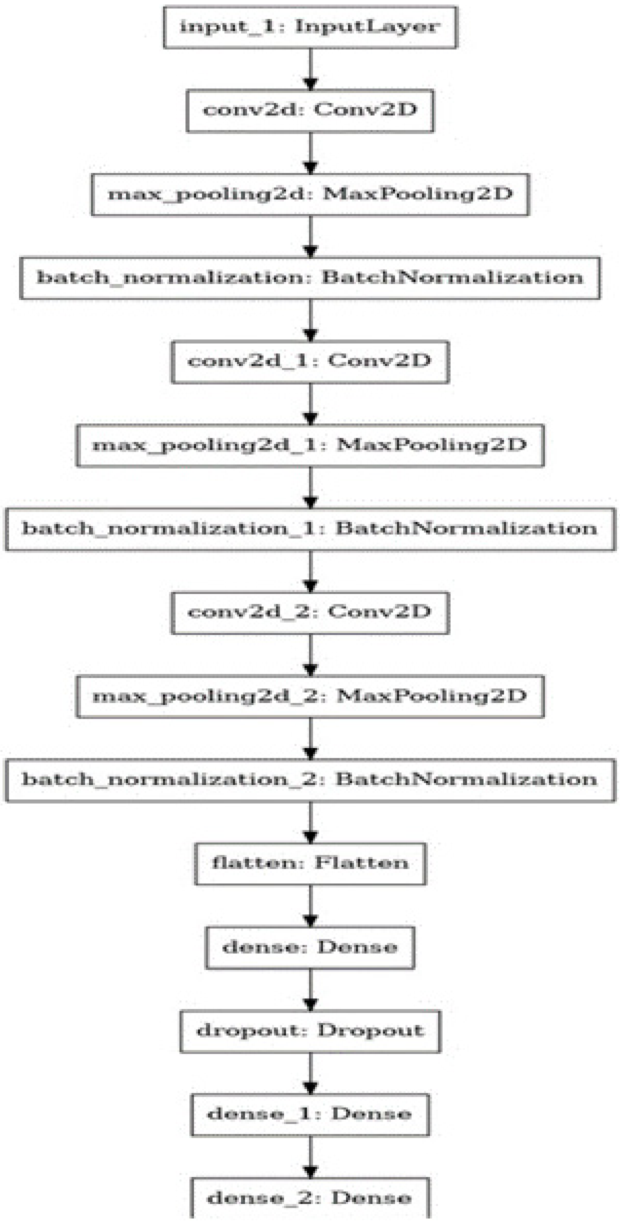

Figure 1. *The stages of machine learning of the CNN model*

As seen in Figure 1 "CNN stages of the machine learning model" that is used for machine learning research in the context of the data set during the processing phase is examined, the density in the layer between the input layer with processes, the identification and classification of taking the picture and RGB codes colors after the decision of the mechanism used in the determination of the correct and incorrect sensitivity is not understood.

In order to analyze a brain tumor detection software and create an installation diagram, first of all, the goals and objectives for which the software will be used have been determined. Not only

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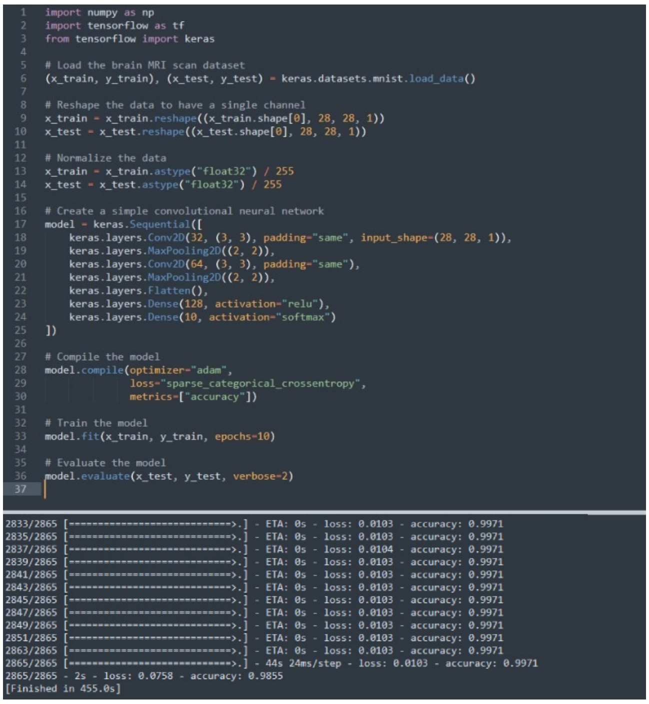
will the software be used to detect brain tumors, or in addition, other brain lesions to detect about how to use the software in accordance with goals and objectives related to the detection and classification of the needed properties were determined. Then, the data set required for the software was collected and various operations were performed on this data set. Here, training and test sets have been created as the two basic sets necessary especially for preprocessing operations on the dataset and making the dataset suitable for learning algorithms.

After this stage, in which training and test sets were created, a suitable learning algorithm was selected for the software. Classification algorithms such as neural networks or support vector machines have been trained on the dataset, increasing its performance in detecting brain tumors. The performance of the trained learning algorithm was evaluated on the test set. At this stage, important metrics such as the accuracy rate of the algorithm and the error detection rate were measured and the performance of the algorithm was evaluated in accordance with these metrics.



```
import numpy as np
import tensorflow as tf
from tensorflow import keras

# Load the brain MRI scan dataset
(x_train, y_train), (x_test, y_test) = keras.datasets.mnist.load_data()

# Reshape the data to have a single channel
x_train = x_train.reshape((x_train.shape[0], 28, 28, 1))
x_test = x_test.reshape((x_test.shape[0], 28, 28, 1))

# Normalize the data
x_train = x_train.astype("float32") / 255
x_test = x_test.astype("float32") / 255

# Create a simple convolutional neural network
model = keras.Sequential([
    keras.layers.Conv2D(32, (3, 3), padding="same", input_shape=(28, 28, 1)),
    keras.layers.MaxPooling2D((2, 2)),
    keras.layers.Conv2D(64, (3, 3), padding="same"),
    keras.layers.MaxPooling2D((2, 2)),
    keras.layers.Flatten(),
    keras.layers.Dense(128, activation="relu"),
    keras.layers.Dense(10, activation="softmax")
])

# Compile the model
model.compile(optimizer="adam",
              loss="sparse_categorical_crossentropy",
              metrics=["accuracy"])

# Train the model
model.fit(x_train, y_train, epochs=10)

# Evaluate the model
model.evaluate(x_test, y_test, verbose=2)

2833/2865 [============================>.] - ETA: 0s - loss: 0.0103 - accuracy: 0.9971
2835/2865 [============================>.] - ETA: 0s - loss: 0.0103 - accuracy: 0.9971
2837/2865 [============================>.] - ETA: 0s - loss: 0.0104 - accuracy: 0.9971
2839/2865 [============================>.] - ETA: 0s - loss: 0.0103 - accuracy: 0.9971
2841/2865 [============================>.] - ETA: 0s - loss: 0.0103 - accuracy: 0.9971
2843/2865 [============================>.] - ETA: 0s - loss: 0.0103 - accuracy: 0.9971
2845/2865 [============================>.] - ETA: 0s - loss: 0.0103 - accuracy: 0.9971
2847/2865 [============================>.] - ETA: 0s - loss: 0.0103 - accuracy: 0.9971
2849/2865 [============================>.] - ETA: 0s - loss: 0.0103 - accuracy: 0.9971
2851/2865 [============================>.] - ETA: 0s - loss: 0.0103 - accuracy: 0.9971
2863/2865 [============================>.] - ETA: 0s - loss: 0.0103 - accuracy: 0.9971
2865/2865 [============================>.] - 44s 24ms/step - loss: 0.0103 - accuracy: 0.9971
2865/2865 - 2s - loss: 0.0758 - accuracy: 0.9855
[Finished in 455.0s]
```

Figure 2. *Artificial intelligence machine learning software code and working section*

In Figure 2, software cross-sectional sample, it was determined that the performance of the learning algorithm trained on the coded data of brain cross-sectional samples with and without tumors was sufficient, and a software installation diagram was created. In this context, the following steps were followed for the process of creating the installation diagram of the brain tumor detection software via artificial intelligence and CNN method.

Firstly, the collection of data through an artificial intelligence-based model, determination of their qualities, classification and verification have been determined as a general study directive. It has been determined which type of brain tumor detection software is. Important information such as the working principle of this software, the necessary hardware and software requirements have been added. The hardware and software systems necessary to run the brain tumor detection software and the application has been run for scanning and testing processes via a computer that can perform high performance according to the working principle and requirements of the software.

In this study, the artificial intelligence-based software is decoded in such a way that while working in a high-performance computer on the GPU, it can also work as a distributed system between the server and a client. In this context, the installation of the hardware and software systems has been completed and the installation and configuration of all the systems necessary for the software to work correctly has been carried out.

At the last stage, after completing the installation of the software for detecting and classifying brain tumors, the software was tested to check whether it was working correctly. This process was carried out to check whether the software is installed and configured correctly and whether it gives the expected results.

In the image in Figure 3 there are images in the size of 240x240 that are used in the training phase for tumor detection and classification on MRI images in the data set. These images have been processed from the machine learning training process onwards and general detection and classification analyses have been carried out until the testing processes.

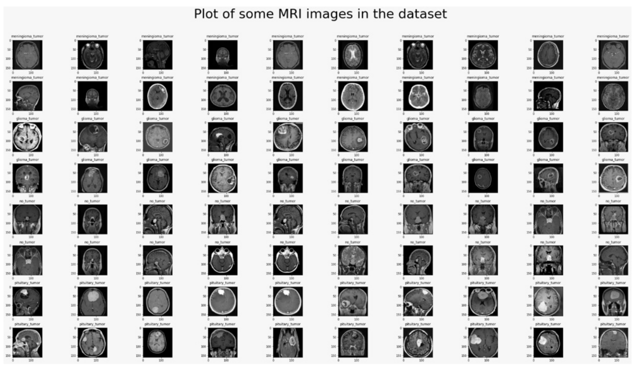


Figure 3. *Tumor detection data classification cross-sectional image*

3. RESULTS

In this study on brain tumor detection using a CNN model trained with an artificial intelligence program, machine learning analysis was conducted. The analysis involved processing a dataset consisting of MRI images and performing detection and classification of tumors. The dataset was divided into training and testing stages, and the process was carried out in two stages. At the first stage of the research, 3 tumor types and

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1 no-tumor structure were detected as a result of the detection and classification processes performed on 2865 MRI. In the second stage of the research, which was determined as a test process, the pituitary tumor was realized as 74 MRI and 18.78%, glioma tumor was realized as 100 MRI and 25.38%, meningioma tumor was realized as 115 MRI and 29.19% and no tumor MRI was realized as 105 MRI and 26.65% on 395 total MRI as seen in Figure 4.

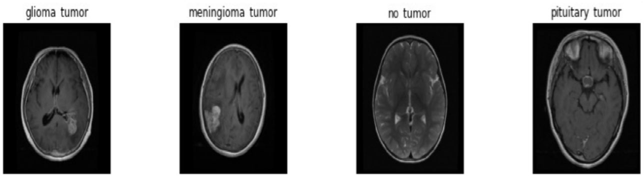

Figure 4. *Tumor detection data validation graphic image*

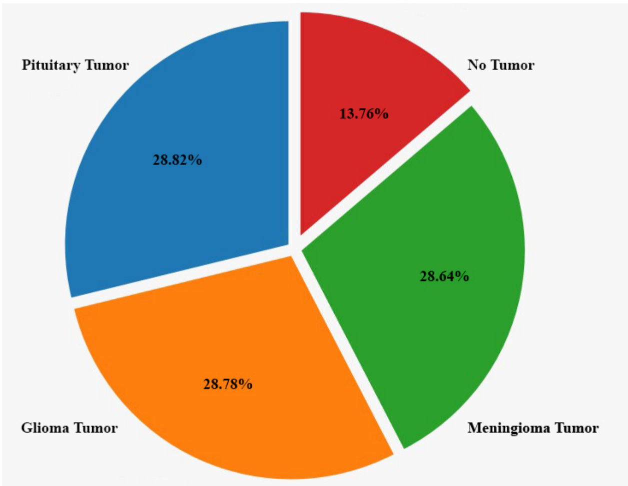

Figure 5. *Percentage distributions of machine learning training tumor detection*

As seen in Figure 5 during the training process, pituitary tumor was 827 MRI and 28.82%, glioma tumor was 826 MRI and 28.78%, meningioma tumor was 822 MRI and 28.64%, and no tumor MRI was 395 MRI and 13.76%.

Table I. *Cross-sectional image of tumor verification and classification*

No	Tumor classification	precision	recall	f1-score	support
0	no_tumor	0.97	1.00	0.99	75
1	glioma_tumor	0.95	0.99	0.97	141
2	meningioma_tumor	1.00	0.94	0.97	139
3	pituitary_tumor	0.99	1.00	0.99	135
	Accuracy	0.98	395		
	Macro avg	0.98	0.98	0.98	395
	Weighted avg	0.98	0.98	0.98	395

As can be seen in the Table I; evaluation of classification results 4 different values emerge. detection of tumored images from 3 with tumored structures and 1 no-tumor structure is observed at the highest value with 98.55% success in terms of sensitivity rate. Among the tumor classification areas, meningioma tumor ranks first as the highest sensitivity rate of 100%.

Another area of research is the "Confusion matrix" measurement. The Confusion matrix is a measurement used to assess the accuracy of the predictions of a given classification model. For example, a classification model attempts to estimate the values of a specific target variable in a data set. According to the actual values of this target variable, it can be evaluated whether the estimates are true or false.

The Confusion matrix is presented in the form of a table for assessing the accuracy of forecasts. This table decodes the relationship between the actual values of the target variable and its estimated values. For example, if the target variable consists of two classes (class A and class B), the confusion matrix will have one row and one column. The rows show the actual values, while the columns show the estimated values. Each cell of this matrix shows a value that intersects with the predicted values of a class of the target variable. For example, if the actual value of a cell is class A and the estimated value is class B, the number of values of class A estimated as B is written in that cell.

Various metrics can be used when evaluating the accuracy of the predictions of the Confusion matrix, classification model. For example, metrics such as accuracy, precision and recall can be calculated. These metrics are calculated based on the data obtained from the Confusion matrix and provide information about the performance of the classification model.

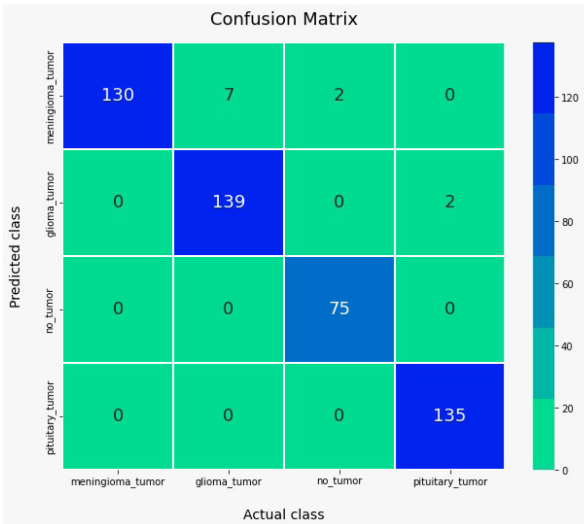

Figure 6. *Cross-sectional image of the tumor detection data Confusion matrix*

Looking at the sectional image Figure 6 as a Confusion matrix; In the model consisting of actual classification values and estimated classification values as two basic variables, meningioma tumor

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130 real 9 is estimated as 139, no-tumor 75, glioma 139 real and 2 deviation values 141, and finally, pituitary 135 real and 2 estimates, out of 137 values, the number of 490 is reached. Since, the findings, which were determined as 99.71% in the training process of the study, were obtained 98.55% accuracy with a loss of 1.16% in the testing process, this research has been comparatively proven with the same value.

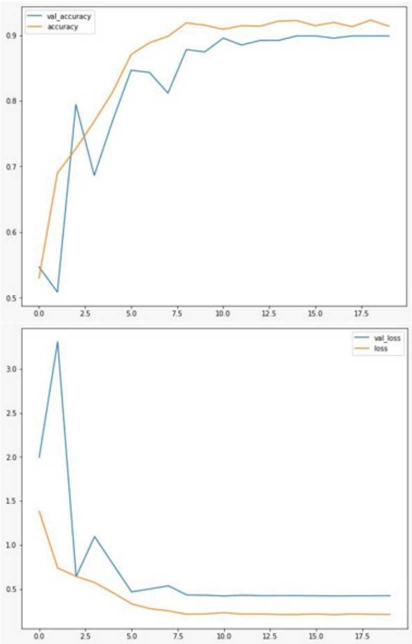

Figure 7. *Estimated value view of CNN model test data*

Using the CNN model, the accuracy loss of the estimates performed on the test data, the training loss (Validation loss) rates indicated in blue and the verification loss rates over time indicated in orange are examined. Accordingly, in Figure 7 the loss of training shows how well the model fits the training data, while the loss of verification shows how well the model fits the new data.

When the data obtained from both graphs are examined, the accuracy values in the first graph are shown in the blue colored unit at the training stage, showing the loss rates on the previously detected tumor status images, while in the orange colored unit, the loss of new test images to the system during verification over time is observed. In this case, it is understood that the accuracy rate is 99.71% and the loss rate is about 1%. In the second graph, it is also understood that the loss levels within the relevant color codes show a rapid decrease based on the loss rates and prove the level of accuracy.

4. DISCUSSION

The global health system, because of the higher percentage of patients per doctor in the health of the employees who have less time to make the decision more accurate diagnostic and treatment protocols possible in the process of the establishment of the possibility of faulty decision-making to reduce risk in the face of developments in the fields of information and communication technologies and engineering considers important to take advantage of. For this reason, qualified solution processes can be provided by combining studies in the field of artificial intelligence with the help of diagnoses made in previous treatments. In recent years, the rapid increase in cancer cases and the low number of trained medical personnel, as well as the high cost of treatment, are factors for the production of alternative solutions. Especially in order to reduce the permanent damage of tumor formations in the brain region, it is important to perform early detection and classification studies in terms of treatment processes.

According to data from previous case studies in the field; Kurup et al. (3064 images from 233 patients) using CNN TensorFlow architecture, they achieved 87% accuracy in the test phase and 92% accuracy in the validation process [30]. Swati et al., studied a method for analyzing MRI images using a pre-trained CNN model. In this study, five additive validation features achieved a 94.82% success rate [28]; Özyurt et al., examined the features of images using the NS-EMFSE method for the detection of brain tumors. They obtained an accuracy rate of 95.62% on 160 MRIs using the MatConvnet library with SVM and KNN classification system [21]. Wozniak et al., proposed a new correlation learning mechanism (CLM) for deep neural network architectures that combines a CNN with a classical architecture. The results show that the CLM model can achieve about 96% accuracy and about 95% precision and recall [31].

Seetha and Raja used the BraTS 2015 dataset consisting of 220 high-grade glioma (HGG) and 54 low-grade glioma (LGG) MR images. They achieved 83.0% accuracy using SVM-based classification and 97.5% accuracy using CNN [32]. Hossain et al. used the BRATS dataset for Brain Tumor Segmentation. They used a total of 207 MRI images, 187 with tumors and 30 without tumors. They achieved 92.42% accuracy using SVM and 97.87% accuracy using CNN [33]. Kachwalla et al. achieved 98% accuracy using the Harvard dataset (66 real human brain MRIs including 22 normal and 44 abnormal images) [34]. Khairandish et al. analyzed 220 brain MRI images in their study. In this context, the accuracy levels were 95% on Deep CNN (DCNN) and 97.5% on the CNN model. The overall accuracy of the hybrid CNN-SVM was calculated as 98.49% [35].

In studies analyzed through the CNN model, which is one of the various classification formats used in tumor detection studies, small-scale data sets are preferred in order to achieve high accuracy. It is thought that various studies in the literature differ significantly from our study for this reason. Because, in order to use large-scale data sets, models with high level of analysis and effective artificial intelligence models should be used.

This study has been prepared to examine the success rate of detection and classification operations using the machine learning method. The research was carried out in a three-month study process in total. As a result of trainings conducted on multiple neural network models, it is observed that the CNN method learns faster, but the transfer model also shows more

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successful results. Against the background of the fact that the results obtained are at the level of 98.55% prediction success rate, there are also contributions of both the method and coding system used and the sample study model based on the visual data sets obtained from the Kaggle library.

In this study model, it is possible to increase the level of success by supporting machine learning through more visual data in order to increase the reliability and accuracy levels. When interpreting the results of a blood test taken as output in the past years, Today, blood test results, if provided along with reference ranges through emerging computing technologies in the near future, especially in cases of cancer in the determination of the test results, artificial intelligence-machine learning methods also aided in the health sector can play a decisive role in the output as it is considered in the light of this study. It is also predicted that in the near future, the health sector, especially by supporting technological innovations and accelerated systems, will be able to shape the common global health model as well as qualified doctor-patient communication. In the research, while 99.71% accuracy was achieved on 2865 MRI images in the training process, 98.55% accuracy was achieved with 1.16% loss in the test process. The performance of our proposed method is considered to be a qualified reference for brain tumor detection and multi-classification studies since high accuracy is obtained as a result of analyzing 2865 MR images.

Compliance with the Ethical Standards

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