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ANALYSIS OF BRAIN TUMOR MENINGIOMA DETECTION SYSTEM DEVELOPMENT USING CONVOLUTIONAL NEURAL NETWORK METHOD MOBILENET ARCHITECTURE

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KEYWORDS	ABSTRACT
brain, convolutional neural network, neural tumors.	This research aims to design a brain tumor detection tool using the MobileNet architecture Convolutional Neural Network method. The CNN method with MobileNet can effectively detect brain tumors via CT-Scan, with more accurate diagnostic results and reduced errors. This method also speeds up diagnostic time and can help remote areas. The MobileNet application is standalone but requires a web server; it can detect meningioma and glioma brain tumors. The training data includes contrast and non-contrast images, with an accuracy level of MobileNet version 3 reaching 100% compared to the Anatomical Pathology examination. Evaluation of the effectiveness of the CNN method provides an understanding of the strengths and weaknesses of this method. The CNN method can potentially improve diagnostic accuracy, time efficiency, and the results of detecting meningioma brain tumors. Analysis of differences in diagnoses before and after using the CNN method provides essential information about the benefits and advantages of its use in clinical practice, including improvements in detection accuracy, sensitivity, and specificity in identifying meningioma brain tumors with consistent and reliable results.

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INTRODUCTION

The growth of cells contained in the human body is something that naturally occurs. However, if cell growth is not controlled, it can cause certain disease disorders (Chadid et al., 2018). Cancer (malignant tumor, neoplasm) is a disease that can arise if there is an uncontrolled growth of abnormal cells in the body. If these abnormal cells grow past normal limits in the body, of course, this can have a harmful impact, which can attack and disrupt the surrounding body parts; even these growths can spread and interfere with the function of other organs (metastases). Extensive metastases are the leading cause of death from cancer. Based on Globocan data for 2020 (Global Cancer Observatory) in Indonesia, there were 396,914 new cases of cancer and 234,511 deaths caused by cancer (Ferlay et al., 2020).

According to Globocan data for 2020, there were 308,102 (1.6%) new cases of cancer, one of which was a brain tumor (Ferlay et al., 2020). Of all cancers worldwide, brain tumors are a newly developing case, ranked 20th among all types of cancer (Flohr & Schmidt, 2016). Based on 2020 data from WHO, brain cancer in Indonesia has reached 1.5% of all cancer cases with a mortality rate of 2.3% (Ferlay et al., 2020).

As one part of the human body, the brain plays a vital role in controlling the entire nervous system. Of course, abnormal cell growth can disrupt the brain's work system, affecting the control of the human body's nerves. In this case, abnormal cell growth in the human brain is known as a brain tumor.

Brain tumors are expansionary lesions that originate in the brain. The abnormal and uncontrolled growth of abnormal cells in or around the brain is a sign of a brain tumor in the body. Brain tumors do not always change into malignant or cancerous tumors. If, at first, a brain tumor appears in the head and then extends to around the brain and head, this is known as a primary tumor. Meanwhile, secondary tumors extend to parts of the human brain originating from other body parts. Until now, the factors that cause tumor disease have not been identified (Baert, 2013).

Tumors that grow not too fast do not impact humans much; this is inversely proportional to tumors with fast growth (malignant tumors), which can cause other abnormal effects (Zaki & Abofarw, 2022). Globally, tumors have become the second most common cause of death after heart disease. Meanwhile, in Indonesia, tumors occupy the fifth position as the deadliest disease after kidney disease, diabetes, stroke, and high blood pressure (Pulvirenti et al., 2021). Another note states that the number of tumor sufferers in developed countries is said to be quite high, but the death rate is relatively small. This is due to the relatively better support of health facilities, such as health services, the number of paramedics, and their supporting equipment, which makes them able to be better at holding back the rate of death among sufferers of this tumor.

Contrary to this, in developing countries, the ratio of death rates is even higher than the number of sufferers. This is because there are still deficiencies in early treatment, so many patients who come to the medical unit are already experiencing high-stage conditions. This makes the recovery process complicated. In addition, the number of paramedics and other supporting facilities is also inadequate, making it more difficult for sufferers to recover.

A meningioma tumor is one of the most common types of tumor found based on expert data at the Tangerang District Hospital. Meningioma is a type of tumor that develops in the meninges, the protective coverings of tissue that surround the brain and spinal cord (Buch & Jain, 2013). Meningiomas are usually benign (not cancer) but can press on essential structures in the brain and cause symptoms such as headaches, seizures, and changes in vision or strength. Treatment options for meningioma may include surgery, radiation therapy, or observation.

The results of the subsequent diagnosis of brain tumors are the condition that there is no tumor, meaning that there is no abnormal cell growth in the body. This could mean a person has a negative cancer diagnosis or another type of tumor.

Diagnosis of brain tumors from image datasets generated from Computed Tomography Scanner (CT-Scan) equipment can only be performed by paramedics with particular expertise. The scientific community has developed various techniques for segmenting and classifying brain tumors. Artificial Intelligence (AI) can help doctors and patients predict brain tumors from CT scan images quickly, accurately, and at an affordable cost. The technique used in artificial intelligence to solve a problem is imitating the intelligence of living things and inanimate objects. Many types of Artificial Intelligence (AI) methods can be utilized in performing image recognition, one of which is by imitating the work of human nerves, which is called deep learning. This technique mimics the fundamental part of the brain (Ahmad, 2017).

The rapid development of Graphic Processing Unit (GPU) technology provides an opportunity for the use of Deep Learning, one of the artificial neural network models that can be used and developed as a tool to assist image recognition. Deep learning is considered to have a high level of accuracy. Several Deep Learning technologies, including the Convolutional Neural Network, can be used for image recognition. As a technology developed from the Multi-Layer Perceptron Method, of course, the

Convolutional Neural Network is better than the Multi-Layer Perceptron Method. The advantage of the Convolutional Neural Network Method compared to the Multi-Layer Perceptron method is the high network depth. These advantages are the reason for applying the Convolutional Neural Network Method as a tool for analyzing image recognition data. Convolutional Neural Network can produce high accuracy and better results than the Multi-Layer Perceptron Method.

Another thing that causes the Multi-Layer Perceptron method to be considered less good than the Convolutional Neural Network Method is that, in the method, data from the results of image recognition processing that has been done needs to be stored. The Multi-Layer Perceptron Method assumes that each pixel is an independent feature. This causes the results to be less good (Putra, 2016).

The Convolutional Neural Network architecture can extract features automatically. VGG16 is a Convolutional Neural Network architecture with 16 layers developed by Simonyan and Zisserman in 2014 (Simonyan & Zisserman, 2014). The VGG16 architecture has proven effective in detecting objects in medical images, including brain tumors. However, the main weakness of VGG16 is its large size, so it requires a long computing time and much memory when running on mobile or embedded devices. Therefore, developing the MobileNet architecture is essential to fix the weaknesses of the VGG16 architecture and produce a more advanced artificial neural network model. Efficient and fast. The MobileNet architecture was developed by Howard and his colleagues in 2017 (Howard et al., 2017), focusing on reducing the number of parameters and convolution operations in a Convolutional Neural Network model. The MobileNet architecture offers a smaller size and faster computation, making it suitable for running on mobile or embedded devices.

In the development of the MobileNet architecture for brain tumor detection, it is necessary to have a PA dataset of medical images by an expert doctor or oncologist to train and test the model; this architecture is designed for use in mobile applications and is the first mobile computer vision model based on TensorFlow. In MobileNet, convolution is replaced with "Deep-Separable Convolution," done in two stages: Depthwise Convolution or Depthwise Convolution. Pointwise Convolution or Point Convolution. Depth Convolution applies a filter to each channel, unlike conventional convolution, which applies a filter to all channels. Pointwise Convolution consists of concatenating the output of Depthwise Convolution. This is also called a 1 × 1 convolution (Howard et al., 2017).

Tumor detection using the Convolutional Neural Network Method is an exciting research topic in the field of medical image processing. Convolutional Neural Network is one of the most widely used types of Deep Learning architectures in image processing because of its ability to perform feature extraction automatically from images. The Convolutional Neural Network Method can be used for tumor detection with better accuracy than traditional methods. However, further research is still needed to develop a better Convolutional Neural Network Method that can be used on a large scale to detect tumors in various medical images (Al et al., 2022).

This research is part of an effort to conduct experiments on developing the Convolution Neural Network Method, which will be applied to analyze the results of Meningioma tumor detection. Several previous studies used the Convolutional Neural Network Method with various architectures, so in this research, development was carried out using a different architecture, namely MobileNet. This architecture was chosen because the MobileNet architecture is lighter than the traditional architecture because it uses depthwise separable convolution to convolve each channel separately. This reduces the number of parameters that need to be trained and makes the model faster and more efficient in image processing. Because it is lighter, the MobileNet architecture can run faster on mobile devices or systems with limited resources. The MobileNet architecture can be scaled for use in a wide variety of image processing applications by resizing the model. This makes MobileNet more flexible and usable on various devices with different sizes and resources.

Based on the description of the background above, this research aims to design a brain tumor detection tool using the MobileNet architecture Convolutional Neural Network method. The development of a better and more accurate detection system can shorten the time needed to diagnose a meningioma brain tumor, reduce misdiagnosis and increase the patient's chances of recovery. "So that this research is beneficial in helping the community recognize a type of brain tumor based on the Convolutional Neural Network Method without requiring expert intervention. It can also enhance healthcare services, contribute to public awareness regarding brain tumor types through the Convolutional Neural Network Method, and with this research, aid in providing quick, accurate, and cost-effective information to the community for detecting the most common type of brain tumor, meningioma tumor.

METHODS

The research method used is Research and Development (RnD). This research aims to develop an object detection system using the Convolutional Neural Network (CNN) Method with the MobileNet architecture applied to a meningioma tumor detection system. Research and Development (RnD) is a method used to make sure products, whether new or developed old products, and to test the effectiveness of these products to make them innovative, productive, and valuable (Sugiyono, 2013). The research and development process includes five steps which can be seen in Figure 3.2 as follows: 1. Information gathering, 2. Product/model design, 3. Expert validation and revision, 4. Product/model trial, 5. Product/model results.

The population in this study was human resources at the Radiology Installation at the Tangerang District Hospital, totaling 25 people based on HR data at the Radiology Installation at Tangerang District Hospital in 2023. The sample used in this study was based on calculations; the number of samples obtained that could be used as respondents were 20 people using CT Scan images of meningioma brain tumor patients. The analytical techniques used in this study were univariate analysis, bivariate analysis, and effectiveness testing.

RESULTS AND DISCUSSION

Validity Test and Reliability Test

MobileNet, which has been developed, can undergo validity and reliability tests on experts and users to evaluate the quality and performance of the model.

Results by Media Experts

Validation for media experts aims to determine the feasibility of the developed media regarding the suitability aspect of MobileNet's appearance. The media was validated on June 13, 2023, by the validator using a questionnaire with a Likert scale of 1 to 4. The results of the assessment by media experts consisted of 4 aspects, namely Usability aspects, Functionality aspects, Reliability aspects, and Data Security aspects. The results of the media assessment by learning media experts are presented in the following table.

Table 1. Results of Media Expert Assessment

Aspect	Score Acquisition	Percentage of Average Score	Category
Usability	14	87.5 %	Very good
Functionality	14	87.5 %	Very good
Reliability	14	87.5 %	Very good
Data Security	10	62.5%	Good

Aspect	Score Acquisition	Percentage of Average Score	Category
Overall Average		81.25%	Very good

Based on Table 1, information is obtained that the assessment of the four aspects by media experts varies. The usability aspect score was 14 out of a total score of 16, resulting in an average score percentage of 87.5%. The score for the functionality aspect is 14 out of a total score of 16, so the average percentage score is 87.5%. The score for the reliability aspect was 14 out of a total score of 16, resulting in an average score percentage of 87.5%. The score for the Data Security aspect is 10 out of a total score of 16, resulting in an average score percentage of 62.5%. Based on the percentage value conversion results, the overall average rating of media experts has excellent validity.

The results of the analysis of media evaluation by media experts in terms of the four aspects can be seen more clearly in the following figure:

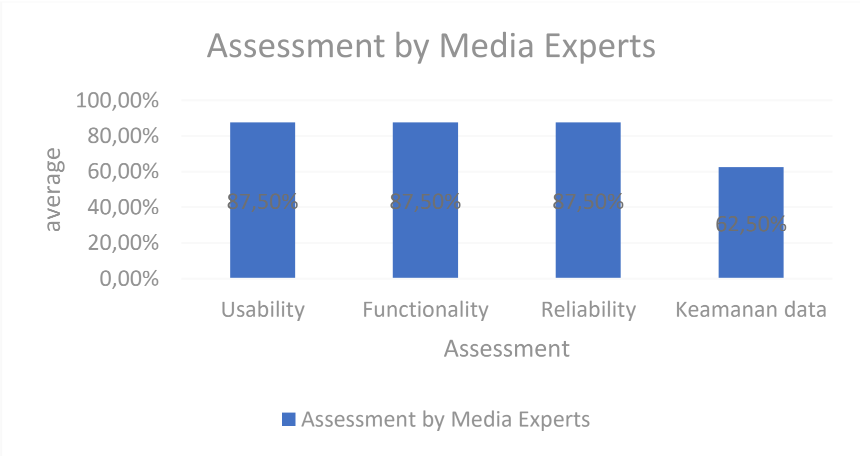

Figure 1. Graph of Assessment by Media Experts

Based on the results of the correlation test of the four aspects, it can be seen more clearly in the following table:

Table 2. Validity Test

Items	r_{Count}	r_{Table}	Information
Items1	0.577	0.950	Invalid
Items2	1.0	0.950	Valid
Items3	1.0	0.950	Valid
Items4	0.870	0.950	Invalid

Based on the output correlations, it is known that the value of r counts for item 1, item 2, item 3, and item 4, respectively, is 0.577; 1.0; 1.0; and 0.870. With a significance of 5%, the r_{table} value is 0.950. Because the value of r counts item2 and item3 > r_{table} (0.950), then in the validity test, it can be concluded that the data is valid. Meanwhile, because the value of r_{counts} item1 and item4 < r_{table} (0.950), the validity test can conclude that the data is not valid.

Based on the results of the reliability test of the four aspects, it can be seen more clearly in the following table:

Table 3. Reliability Test

Cronbach's Alpha	N of Items
0.650	4

Based on the output above, it is known that there are four items with a Cronbach's Alpha value of 0.650. Because Cronbach's Alpha value is 0.650 > 0.6, it can be concluded that the four items are reliable or consistent.

Results By User

Validation by the user aims to determine the feasibility of the developed media in terms of the suitability aspect of MobileNet's appearance. The media was validated using a questionnaire equipped with a Likert scale ranging from 1 to 4. Based on the results of the correlation test of the four aspects, more clearly can be seen in the following table:

Table 4. Validity Test

Items	r_{count}	r_{table}	Information
Items1	0.574	0.334	Valid
Items2	0.671	0.334	Valid
Items3	.498	0.334	Valid
Items4	0.448	0.334	Valid
Items5	.445	0.334	Valid
Items6	.650	0.334	Valid
Items7	0.584	0.334	Valid
Items8	0.552	0.334	Valid
Items9	0.685	0.334	Valid
Items10	.650	0.334	Valid
Items11	0.698	0.334	Valid
Items12	0.606	0.334	Valid
Items13	0.581	0.334	Valid
Items14	.440	0.334	Valid
Items15	.630	0.334	Valid
Items16	0.468	0.334	Valid
Items17	0.653	0.334	Valid
	0.574	0.334	Valid

Based on the output correlations, it is known that the significance of 5% of the 35 samples produces an r-table value of 0.334. Because the value of r_{counts} item1 to item17 > r_{table} (0.334), then in the validity test it can be concluded that all data is valid.

Based on the results of the reliability test of the four aspects, it can be seen more clearly in the following table:

Table 5. Reliability Test

Cronbach's Alpha	N of Items
0.875	17

Based on the output above, it is known that there are four items with a Cronbach's Alpha value of 0.875. Because Cronbach's Alpha value is 0.875 > 0.6, it can be concluded that the 17 items are reliable or consistent.

Normality test

The normality test tests whether the data has a normal distribution. The normal distribution is symmetrical, with peaks centered around the mean, and has tails that decrease symmetrically in both directions. The normality test results based on the results of checking using MobileNet are as follows.

Table 6. Normality Test Results

Type	Sig.	Information
Version 1	0.048	Normal
Version 2	0.005	Normal
Version 3	0.000	Normal

Source: (Shapiro-Wilk)

The data in Table 6, which refers to Shapiro-Wilk, shows the value of Sig. Version 1, version 2, and version 3, respectively, are 0.048, 0.005, and 0.000. Because all values are at a significant level $\alpha > 0.05$ ($p > 0.05$), the data obtained for these values are normally distributed. Based on the results of the normality test, it can be seen that the significance value for each version is determined by the Shapiro-Wilk test and that the data distribution meets the normality assumption. This means there is an influence between the MobileNet architecture Convolutional Neural Network (CNN) method to detect meningioma brain tumors.

Homogeneity Test

The homogeneity test tests whether the variation or dispersion of two or more groups or data samples is the same. In the context of statistics, homogeneity refers to the similarity or consistency of the dispersion between the groups. The homogeneity test results based on the results of checking using MobileNet are as follows.

Table 7. Homogeneity Test Results

Levene Statistics	Sig.	Information
75,637	0.064	Homogeneous

Data in Table 7. It is known that the significance value (Sig.) is 0.064. Because of the value of Sig. 0.064 > 0.05, it can be concluded that the data variance is the same or homogeneous. It is also known that the statistical level value is 75.637, so it can be seen that the difference in variation between the groups is 75.637.

Paired sample t-test

Paired sample t-test compares the averages of two related or paired samples. These samples have a close relationship or dependence on one another. The results of the Paired sample t-test based on the results of checking using MobileNet are as follows.

Table 8. Results of the Paired Sample T-test

Description	t	df	Sig. (2- *tailed*)
Version 1 – Version 3	-6,682	19	0.000
Version 2 – Version 3	-5,072	19	0.000

Based on the data in Table 8, it is known that the value of Sig. (2-) Versions 1-versions three and 2-versions 3 are 0.000 < 0.05, then H_0 is rejected, and H_a is accepted. So it can be concluded that there is an average difference between the results of image checking for each application version, which means that there is an increase in detection with a high percentage of accuracy in the application. It is known that $t_{arithmetic}$ Version1-version3 is -6.682. Moreover, Versions 2-version 3 is -5.072. In this context, a negative t_{count} value can have a positive meaning. It is known that the calculated df for both is 19, and the significance value $\alpha = 0.05$, then the t_{table} is 1.729. Thus because the calculated value is $6.682 > t_{table}$ 1.729 and $5.072 > t_{table}$ 1.729, it can be concluded that H_0 is rejected and H_a is accepted. So it can be concluded that there is an increase in detection with a high percentage of accuracy so that it is feasible to be used in supporting the diagnosis and treatment of patients with meningioma brain tumors.

Design Analysis of Convolutional Neural Network (CNN) MobileNet Architecture.

Cancer is a disease characterized by the uncontrolled growth of abnormal cells. Normal cells develop and divide regularly according to the body's needs. However, in the case of cancer, the cells undergo genetic changes or mutations that interfere with standard cell growth regulatory mechanisms (Tandel et al., 2019). Under normal conditions, cells die and are programmed to be replaced by new cells. However, in the case of cancer, the abnormal cells continue to grow and divide without control, forming masses or tumors that can invade surrounding tissues (Zaki & Abofarw, 2022).

Diagnosing brain tumors from image datasets generated from Computed Tomography Scanner (CT-Scan) equipment can be performed by paramedics with particular expertise. Rapid developments in technology and innovation have provided great opportunities for using Deep Learning by Graphic Processing Unit (GPU) technology to perform high-level computing to increase the efficiency of processing large amounts of data at high speed. The Graphic Processing Unit (GPU) enables the training of artificial neural network models to be carried out in parallel, thus speeding up the training process and data processing.

One of the Deep Learning methods used is the Convolutional Neural Network (CNN). The main advantage of Convolutional Neural Networks (CNN) in image recognition is the ability to automatically extract essential features from images, reducing the need for time-consuming and complex manual feature extraction. In addition, Convolutional Neural Networks (CNN) can also study hierarchical features at various levels of abstraction, so they are able to recognize complex patterns in images with a high degree of accuracy (Zhang et al., 2018).

Based on these facts, the authors have developed a meningioma brain tumor detection system using the Convolutional Neural Network (CNN) method with the MobileNet architecture. The application is applied to the Radiology Service Installation of Tangerang District Hospital. The sample used in this study was an axial CT scan of the brain. The data used in this study were taken from image storage in the RSU Kab's PACS system. Tangerang. The sample for measurement is an image of a slice or slice showing the structure: the brain cortex, brain lobes, ventricles, and other parts. Each slice contains information about tissue density within the brain, including the area affected by the meningioma tumor.

The Convolutional Neural Network (CNN) model was built using the MobileNet architecture. In the process of making the Convolutional Neural Network (CNN) model program, parameters are used to control the functioning of the MobileNet architecture in order to produce the proper detection of meningioma brain tumors. These parameter settings include the epoch parameter (10). The determination of layers in MobileNet has a basic structure consisting of convolution layers, batch normalization, and activation functions. Some versions of MobileNet also have residual blocks or other unique feature extraction mechanisms. The layer selection can be adjusted according to the needs and intended use in CT-Scan image processing.

Based on the training results of the Convolutional Neural Network (CNN) method with the MobileNet architecture, an epoch is an iterative step in training a model with existing data. Epoch measures the extent to which the model learns from the given data. The results of this model training produce a confusion matrix such as accuracy, precision, and recall at each epoch. These metrics provide information about the model's performance at each training stage.

Having a meningioma brain tumor detection system using the Convolutional Neural Network (CNN) method with the MobileNet architecture can help simplify and speed up the process of detecting meningioma brain tumors. The application is applied to the Radiology Service Installation of Tangerang District Hospital.

Level in Detecting Meningioma Brain Tumors.

In this study, a diagnostic evaluation was carried out as an assessment step for the deep learning model of the Convolutional Neural Network (CNN) method of MobileNet architecture using three versions of MobileNet, namely MobileNetV1, MobileNetV2, and MobileNetV3, after going through the training and testing process using data sets. Diagnostic tests were performed on 200 CT-scan images of the axial head consisting of 100 CT-scan images of Meningioma Brain Tumors and 100 CT-Scan images of no_tumor. The results of the classification will then be compared with the gold standard results of pathological anatomy (PA). Evaluation of this diagnostic test is based on the accuracy, sensitivity, and specificity level.

Diagnostic test results show that the MobileNet architecture Convolutional Neural Network (CNN) method has excellent performance in detecting the presence of meningioma brain tumors (Pham et al., 2019). This model has high accuracy, sensitivity, specificity, and positive predictive value (NDP). That is, this model can recognize and classify meningioma brain tumors with high accuracy, has good sensitivity in detecting positive tumors, has a high level of specificity in identifying negative tumors, and provides an excellent positive predictive value (NDP) in indicates the presence of a meningioma brain tumor.

The results of the MobileNetV1, MobileNetV2, and MobileNetV3 architectural tests on CT-Scan image testing data for meningioma brain tumors show that the prediction success is genuinely positive. The model correctly classifies the meningioma brain tumor image as positive and the no-tumor image as unfavorable. Abnormalities in the brain that can be seen on brain images include the presence of abnormal masses or lumps, changes in brain size or shape, bleeding, increased or decreased intracranial pressure, dilated brain ventricles, changes in the subarachnoid space or brain ventricles, and impaired neurological function (Yousaf et al., 2020). The level of accuracy of the MobileNet architecture of the three versions in detecting meningioma brain tumors is based on data from checking CT-Scan images using the MobileNet architecture Convolutional Neural Network (CNN) application that results in an average difference between the results of checking the image of each application version, which means there is an increase detection with a high percentage of accuracy in the application. It was concluded that the differences in the results of meningioma detection using the Convolutional Neural Network (CNN) method of the MobileNet architecture could refer to results that were more accurate, sensitive, or specific in detecting meningioma brain tumors. MobileNet Version 3 architecture produces the highest level of accuracy among other versions, 100%.

Methods Assessment of meningioma brain tumor detection development using the Convolutional Neural Network (CNN) MobileNet Architecture method was tested for validity and rehabilitation involving validation experts. In addition to a performance assessment on the MobileNet Architecture Convolutional Neural Network (CNN) deep learning model, an assessment was also carried out using brain tumor detection applications. Respondents filled out a questionnaire sheet by conducting a product assessment by applying a feasibility level measurement with aspects such as usability, functionality, reliability, and data security (Mulyawan et al., 2021).

The data obtained shows the results in the form of the Usability aspect, which gets a score of 87.5%, the Functionality aspect of 87.5%, the Reliability aspect of 87.5%, and the data security aspect of 62.5%. Based on the percentage score conversion, the average overall rating of media experts has excellent validity. Although the data security aspect received a slightly lower rating, overall, media experts gave it a high rating. Using the MobileNet architecture in a meningioma brain tumor detection system has proven effective in this context. This model can recognize complex patterns in images, improve performance through iterations, and produce accurate and consistent predictions. Thus, MobileNet significantly contributes to image recognition and analysis to support diagnosing and treating patients with meningioma brain tumors.

Meningioma Brain Tumor Detection System Using the MobileNet Architecture Convolutional Neural Network Method.

This study involved 35 respondents who were Heads of Radiology, Radiology Doctors, Neurosurgeons, Pathological Anatomy Doctors, Medical Physicists, and Radiographers at Tangerang

Hospital. The respondent's performance assessment aims to compare the feasibility of detecting meningioma tumors using the MobileNet architecture Convolutional Neural Network method.

The Convolutional Neural Network (CNN) Method with the MobileNet architecture has also been tested involving media experts. The assessment results by media experts show that the application has a high feasibility level in usability, functionality, reliability, and data security. This shows the potential of this application as an effective tool in supporting the diagnosis and treatment of brain tumors.

This model can recognize complex patterns in images, improve performance through iterations, and produce accurate and consistent predictions. Thus, MobileNet significantly contributes to image recognition and analysis to support diagnosing and treating patients with meningioma brain tumors.

Meningioma detection using the Convolutional Neural Network (CNN) MobileNet architecture method refers to results that are more accurate, sensitive, or specific in detecting meningioma brain tumors compared to other detection methods, and this has been compared with Anatomical Pathology (PA) results of 100%. This application improves the process of detecting actual meningioma tumors on brain images, resulting in more precise and informative results. The effectiveness of these applications is related to the identification of tumor edges, separation of tumors from other brain structures, or improvements in the recognition of tumor characteristic patterns. In addition, the MobileNet architecture Convolutional Neural Network (CNN) method provides better results in differentiating various brain structures, such as the cortex, brain lobes, ventricles, and other parts.

So the application is feasible to support diagnosing and treating patients with meningioma brain tumors. This research is in line with research (Hastomo & Sudjiran, 2021), which has succeeded in conducting training and testing of brain tumor image data with excellent accuracy values so that the model can be used to predict brain tumor images with unknown labels. Another research that is aligned is research (Winnarto et al., 2022) which proves that the MobileNet V3 method can automatically perform image extraction compared to the image classification method used previously, which had to perform image extraction separately. Besides that, the method is also more efficient, especially for memory and complexity.

CONCLUSION

Based on the research and discussion results, the following conclusions are obtained: 1) This research has succeeded in designing a brain tumor detection tool using the Convolutional Neural Network Method with the MobileNet architecture. The development of this detection system aims to increase accuracy and efficiency in diagnosing meningioma brain tumors. With this tool, diagnosis time can be shortened, misdiagnosis can be reduced, and the patient's chances of recovery can be increased. Implementing the Convolutional Neural Network (CNN) Method with the MobileNet architecture can provide a better and more accurate detection system in the fight against meningioma brain tumors. 2) The Convolutional Neural Network (CNN) method can detect brain tumors using CT-Scan images. By comparing the effectiveness of diagnosis using the Convolutional Neural Network Method with the MobileNet architecture with conventional methods such as CT-Scans interpreted by medical experts, it can be concluded that the Convolutional Neural Network (CNN) Method can provide more effective diagnosis results. This method can improve accuracy in detecting meningioma brain tumors, reduce diagnosis time, and minimize diagnostic errors. The Convolutional Neural Network Method can provide convenience for underdeveloped areas; for example, the doctors are not on standby. 3) The application system developed is independent but requires a server that is on or in the sense that it can run a web system so that it can be accessed by patients/health workers. 4) The MobileNet application can read/detect meningioma brain tumors and gliomas. This means this application can read not only one type of disease (meningioma) but also other types of tumors, according to training data. 5) The training data provided in the application is contrast and non-contrast, so the accuracy of the CT-Scan is contrast and non-contrast. The level of accuracy in version 3 of MobileNet is 100% with comparison, namely the results of an Anatomical Pathology (PA) examination. 6) Evaluation of the effectiveness of the Convolutional Neural Network Method in detecting meningioma brain tumors provides an understanding of the strengths and weaknesses of this method. The results of this evaluation form the basis for determining whether the use of the Convolutional Neural Network (CNN) Method is an effective and reliable option in medical practice for the detection of meningioma brain tumors. The Convolutional Neural Network (CNN) Method can improve diagnostic accuracy, time efficiency, and the detection results of meningioma brain tumors. 7) By analyzing the difference between the results of the diagnosis before and after the intervention of the Convolutional Neural Network (CNN) Method, we can evaluate the contribution of this method in improving the quality of the diagnosis of meningioma brain tumors. The results of this analysis provide important information about the benefits and advantages of using the Convolutional Neural Network Method in clinical practice. The Convolutional Neural Network (CNN) Method can improve detection accuracy, sensitivity, and specificity in identifying meningioma brain tumors and provide more consistent and reliable results.

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