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Automated Screening of Brain Disorders: A Machine Learning Model for MRI Classification

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Abstract

This study investigated the potential of using convolutional neural networks (CNNs) for diagnosing brain diseases based on MRI scans. The aim was to compare the accuracy of CNNs to clinician diagnoses and explore their limitations. In the course of the research, the following theoretical methods were used (literature analysis, generalisation); diagnostic (anamnestic survey, the use of MRI); empirical (study of the experience of medical organisations, regulatory documentation); methods of mathematical statistics and deep machine learning. A high-performing CNN model was developed, exhibiting excellent accuracy for specific diseases such as dementia with Lewy bodies. However, challenges were identified with distinguishing meningiomas and ependymomas, suggesting the need for further training data and refinement. These results, together with the conclusions of the works of other authors, continue the path to the implementation of quality education and artificial intelligence in clinical settings. The possibilities of using AI in neurosurgery and neurology are expanding more and more. The main areas of application are diagnostics, models of outcomes and treatment. Further research should focus on improving AI techniques, increasing databases and involving more patients for each of the diseases, including a larger control group.

Keywords: Machine Learning, Artificial Intelligence, Diseases of the Nervous System, Neurosurgery, Diagnostics

1. Introduction

Neuroradiology has gradually moved from a strictly anatomical discipline to a discipline combining anatomy and physiology. As far back as the 1940s, physiological parameters similar to those observed during cerebral angiography have a priority place in the diagnosis of neurological diseases, especially tumors. There was no real movement towards physiological imaging before the clinical introduction of MRI. Although most efforts to find visualizing expressions of cellular, biological and genetic markers are carried out using MRI, current methods are still too few and primitive to allow us to use MRI as the only means of identification and diagnosis, quantification of these processes These answers will be found in the coming years and that many of these advances will first appear in radiology [1].

Magnetic Resonance Imaging (MRI) is a non-invasive technology that produces detailed three-dimensional anatomical images of the body using a combination of a large magnet, radio waves, and computer technology. The process begins with the generation of a high-frequency radio frequency (RF) signal, which is then transmitted to the patient's body, causing hydrogen atoms to align with the magnetic field. Once the RF signal is deactivated, the hydrogen atoms return to their original positions and emit radio signals. The MRI machine captures the data and transforms it into a visual representation of the bodily portion being studied. Nevertheless, magnetic gradients are essential for spatial encoding in MRI because the equipment creates a strong magnetic field around the patient and uses magnetic gradients to differentiate between various tissues based on their distinct magnetic characteristics. This distinction is crucial for creating intricate pictures of the body's interior anatomy.

Meanwhile, the radio waves are mathematically reconstructed, and complex algorithms analyze this data to turn it into a detailed three-dimensional picture. MRI includes producing RF signals and using mathematical algorithms to create detailed pictures of the body's interior anatomy on a screen. This illustrates the impressive collaboration of physics, engineering, and computer science in medical imaging [2]. Demand for the use of MRI is rapidly increasing not only in clinical settings but also in brain research and pharmaceutical development. Therefore, machine learning technologies are needed to automate the process of analysing MRI images [3], [4].

The complexity of analysing MRI data lies in the problems of communication and signal processing. After all, brain signals are non-stationary and have a low amplitude, which leads to certain difficulties. Other factors that contaminate these signals are noise and artefacts. This field is interdisciplinary, bringing together the principles of physics, computer science, and computer graphics to solve medical imaging problems. The study of MRI image analysis, including the use of machine learning and deep learning algorithms, is increasingly being studied in science due to advances in computing [5]. Key techniques such as the Fourier transform, which is essential in modern MR image formation, and Convolutional Neural Networks (CNNs), which enhance image resolution and quality, play pivotal roles.

A more dependable technology for evaluating biomedical pictures is required to assist doctors more effectively [6], [7], [8]. When working with medical data, especially brain models, the professional is prone to interpretation errors due to the complexity, so during radiography, approximately 3-5% of errors and inconsistencies occur every day. This required new methods to help doctors analyse data efficiently. As computing power increases and the quality of medical data improves, interest in using advanced algorithms has increased [9], [10].

The aim of the study was to compare the accuracy of the neural network diagnosis with the disease already established by doctors, and to test the current method of examination on healthy people. The authors set the task of investigating the possibility of conducting a qualitative assessment of convolutional neural systems, describing neurosurgical shortcomings and problems based on MRI images.

2. Related Works

D. Hassabis et al. [11] pointed out the close historical connection between neuroscience and artificial intelligence, but in the current environment, there is a slight decrease in this interaction and dependence. A. Segato [9] delved into the realm of artificial intelligence and its applications in addressing brain-related disorders. In their systematic review, they explored various AI-driven approaches and technologies aimed at diagnosing and treating brain diseases. K.V. Lipianina-

Honcharenko [12] introduced an innovative approach to forming human resources for short-term projects using artificial intelligence. The author's work proposes an intellectual method for assembling project teams efficiently. This method harnesses the power of AI algorithms to match skills and expertise with project requirements, ensuring the successful execution of short-term initiatives.

The authors, I.H. Zinchenko and O.V. Lavdanska [13], examined contemporary technologies created to assess the efficiency of digitalization efforts in organisations. The research by A. Magauiya et al. [14] focuses on the legal implications of intellectual property generated with the use of artificial intelligence. The report analyses the regulatory procedures of developed nations in this field and highlights deficiencies in current laws. The authors analyse the regulatory procedures of developed countries and also highlight the shortcomings of the current legislation. T.O. Prokopenko and Y. Povolotskyi [15] have introduced a detailed set of criteria for assessing the efficiency of IT projects. In addition to analysing current methods and indicating shortcomings in covering the various effects of technology implementation, their proposed methodology includes technical, economic, social, organisational, and environmental variables for a comprehensive assessment.

A.E. Bedelbayeva and G.K. Lukhmanova's [16] study offers a detailed examination of the key developments, obstacles, and potential outcomes of Kazakhstan's emerging biofuel sector. In their work, the researchers reveal the problems of raw material supply, technological limitations, a lack of financial incentives, and the inadequacy of coordinating state policy with industrial growth. A. Barlybayev and A. Sharipbay [17] detail the architecture and functionality of an intelligent computer-based system aimed at enhancing student knowledge acquisition and assessment within educational environments. The core components of the system, including the knowledge database, student interface, and instructor controls are explained in depth. Underlying algorithms rooted in fuzzy logic and neural networks that enable adaptive learning, personalized feedback, and automated evaluation are also delineated.

3. Methodology

In the course of the research, the following theoretical methods were used (literature analysis, generalisation); diagnostic (anamnestic survey, the use of MRI); empirical (study of the experience of medical organisations, regulatory documentation); methods of mathematical statistics and deep machine learning. During the study, the MRI images were identified and classified by a classifier that was trained using an appropriate training dataset.

For the classification of biomedical images, the previously mentioned convolutional neural network architecture was used. The neural network architecture comprises several layers, such as the input layer, convolutional layer, pooling layer, and fully connected layers. The communication pathways between layers involve transmitting feature maps from the output of one layer to the input of the next. During feature extraction, the convolutional layers use filters to extract features from the input image, while the pooling layers downsample the image to reduce computation. The information is encoded in the learned filters and the weights of the fully connected layers, which make the final predictions based on the extracted features. The classification performance for each disease category was evaluated using confusion matrices and common information retrieval metrics. The results revealed the ability of the model to accurately decode the disease state from the encoded MRI data. As a result, there is a qualitative development of the biomedical image before performing the classification task [8]. This object of the neural system makes an adequate assessment of local characteristics, with the aim of grouping them according to biomedical features. It is also a redesigned version of the traditional neural structure architecture for biomedical image differentiation and has provided excellent performance and accurate results in previous studies. The convolutional neural network structure has five layers, three maximum unification layers, two average unification layers, two normalization layers, a single concatenated layer, and three absolutely fixed layers.

The study was conducted using MRI images of 317 patients of both sexes aged 15 to 70 years. 260 patients had a neurological or neurosurgical disease, 57 subjects did not have brain diseases and other chronic pathology and were assigned to the control group. Patients with brain diseases were divided into 5 groups depending on the type of pathology (Figure 1).

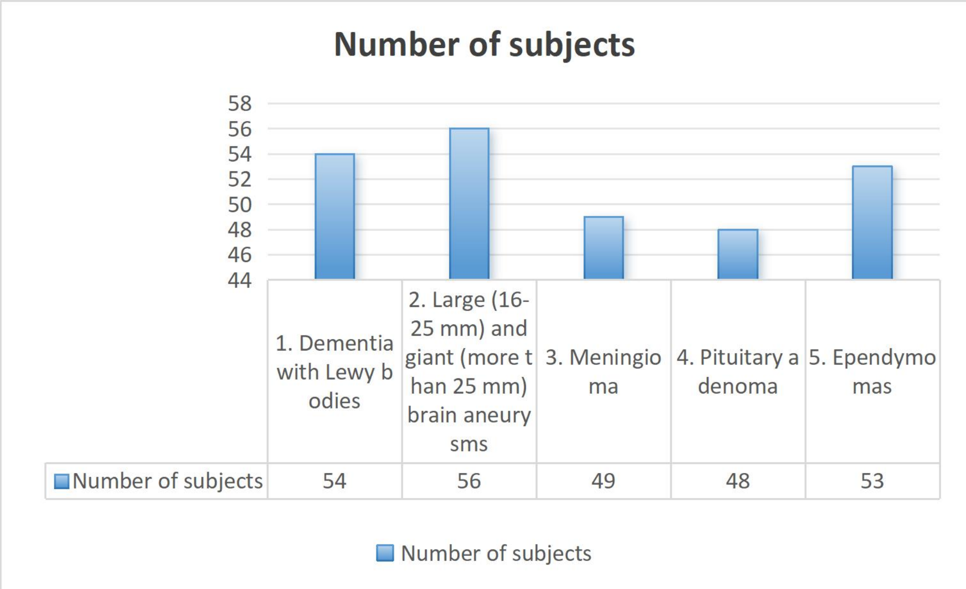

Figure 1. Health Disorders and Number of Patients in Each Category

Participants had to meet the criteria described in Table 1 to be accepted into the study.

Table 1. Criteria for Inclusion and Exclusion of Patients

Exclusion	Inclusion
Participants with an unstable condition requiring urgent medical care	The age of the patient is from 15 to 70 years inclusive, having an early confirmed brain disease
Children under 15	Absence of absolute contraindications to the examination
Participants who underwent neurosurgical intervention prior to the study	Consent of the patient or his legal representatives to conduct the examination

A three-step encoding workflow methodology has been used, which involves method selection by signal characteristics, parameter optimization by error metrics, and encoding optimization by information content.

After analysing the MRI images, the neural network compared these results with the diagnosis already established by doctors, based on which the sensitivity and specificity of the method were determined. Sensitivity was defined as the proportion of positively classified cases among the total number of positive cases [18]. The MRI images were taken using a Canon VANTAGE ELAN Magnetic Resonance imaging machine (Figure 2). The experiments were carried out on an Intel processor (i7-9700) with 32 GB of RAM. The analysis of brain diseases was carried out for 15 months on the basis of several medical institutions. The criteria for inclusion and exclusion from the study are shown in Figure 2.

Figure 2. Canon VANTAGE ELAN Magnetic Resonance Imaging Machine

The study also focused on developing a convolutional neural network (CNN) model for image classification of MRI scans, specifically for the detection of neurological diseases. The CNN architecture consisted of an input layer that accepted the MRI images, followed by convolutional layers that extracted features from the images. To ensure the model's ability to generalize to new data, 5-fold cross-validation was used. The dataset was divided into five groups, with each group used in turn for validation while the remaining groups were examined.

4. Results and Discussion

The described structure is characterized by high efficiency and quality. The sensitivity of the method ranged from 81.6% to 100% depending on the group of subjects. The number of correctly established diagnoses in each group is indicated in Table 2. The sensitivity of the method for each group of diseases is shown in Figure 3.

Table 2. The Number of Correctly Established Diagnoses in Each Group

Group Number	Disease	The Number of Patients with a Correctly Established Diagnosis
1	Dementia with Lewy bodies	54
2	Large (16-25 mm) and giant (more than 25 mm) brain aneurysms	56
3	Meningioma	40
4	Pituitary adenoma	47
5	Ependymomas	45
Total		260

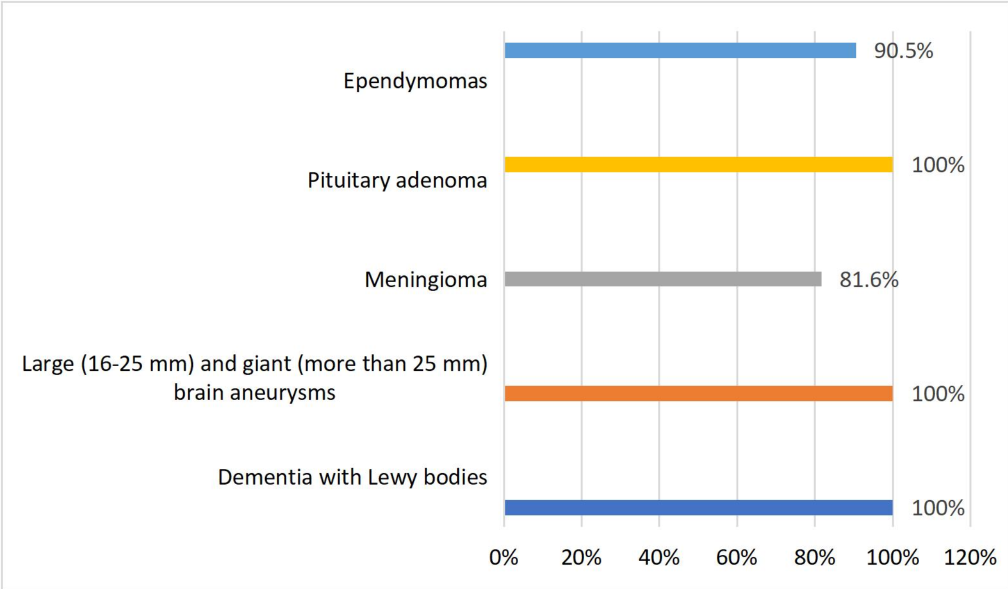

Figure 3. Sensitivity of the Method for Each Group of Studied Diseases, %

The specificity of the method for each group of diseases is shown in Figure 4 and ranges from 80.2% to 100%. The best results were achieved in the diagnosis of dementia with Lewy bodies, large and giant aneurysms and pituitary adenomas.

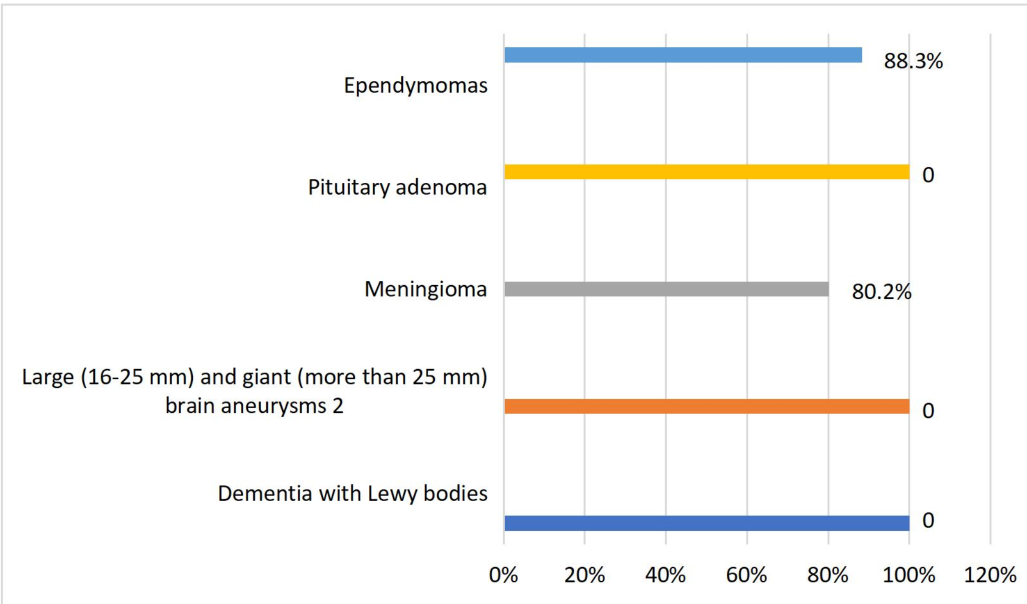

Figure 4. Specificity of the Method for Each Group of Studied Diseases, %

For Dementia with Lewy bodies, the confusion matrix revealed 54 true positives, 0 false positives, 3 false negatives, and 57 true negatives. The model's precision of 100% indicates that all positive predictions corresponded to true positives, highlighting the accuracy of the model. The recall rate of 94.7% highlights a strong true positive rate, showcasing the model's precision in identifying the condition (Figure 5).

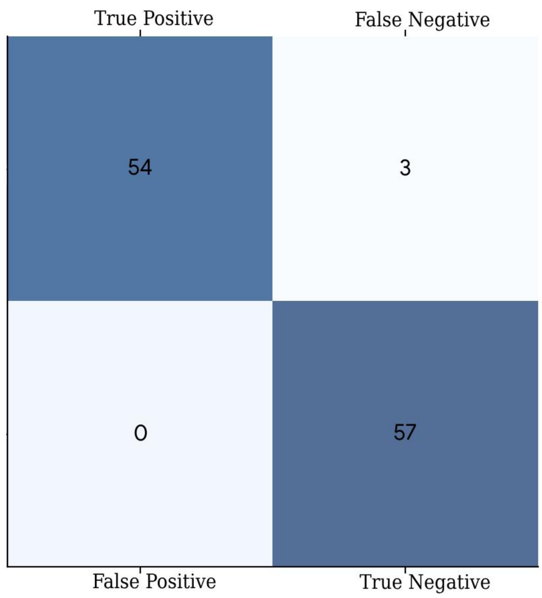

Figure 5. Dementia with Lewy Bodies Confusion Matrix

Precision is crucial in healthcare environments to avoid needless treatments or inaccurate diagnoses. If the model detects Dementia with Lewy Bodies in someone, it is quite probable that they have the disorder. Furthermore, the model's excellent recall rate of 94.7% suggests that it seldom fails to identify actual instances of Dementia with Lewy Bodies. 56 giant aneurysms were correctly identified as positive cases; 1 false positive was identified, and there was no missed aneurysm case. The model's accuracy was 98.2%, which shows that it correctly decoded the aneurysm condition, and its 100% flawless recall rate shows that it can correctly interpret disease information in this category (Figure 6).

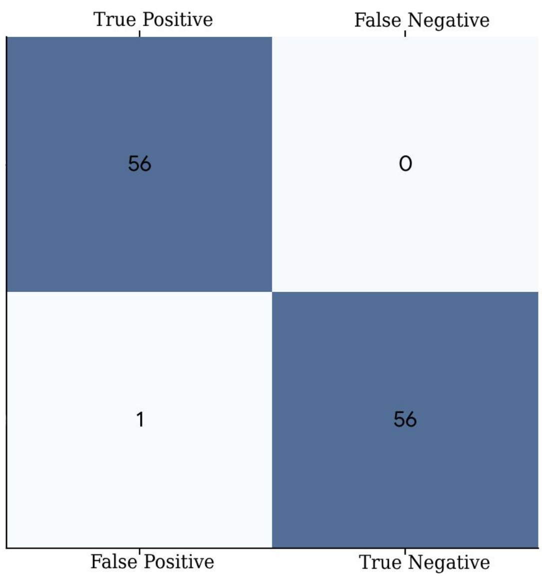

Figure 6. The Confusion Matrix for Large and Giant Aneurysms

The confusion matrix for meningiomas indicated 33 true positives, 11 false positives, 7 false negatives, and 53 true negatives. The model's accuracy of 75% suggests that it struggled to reliably identify the meningioma disease state due to noisy encoding. The recall rate of 82.5% revealed insufficient transfer of pathogenic information, showing constraints in the coding process (Figure 7).

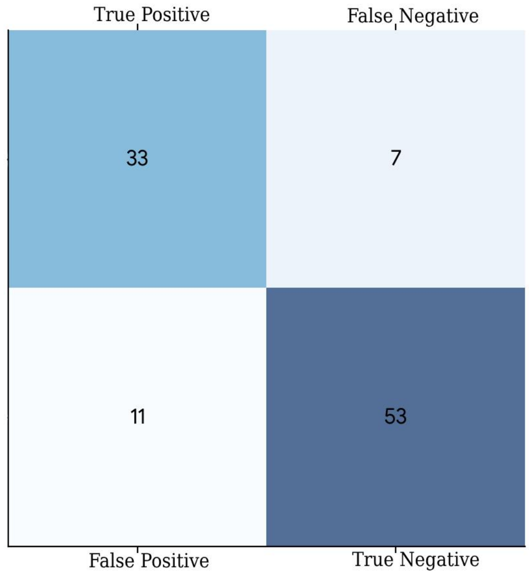

Figure 7. The Confusion Matrix for Meningiomas

It is important to understand the shortcomings of this method, as the reduction in accuracy results in a significant number of false positives, leading to unnecessary testing and associated patient anxiety. To enhance the model's accuracy, a comprehensive study of the data should be carried out, focusing on the attributes of false positives and false negatives. This method can expose any prejudices or constraints in the training data, allowing for adjustments to the dataset to improve the model's effectiveness. Furthermore, testing other algorithms or modifying current ones might enhance the accuracy of differentiating meningioma from other disorders. Optimisation may include modifying parameters and considering other methods to improve the model's precision in identifying meningioma. By including more medical data, like particular biomarkers or imaging modalities, the model's ability to diagnose meningioma can be improved.

The model correctly identified 47 cases of pituitary adenomas, made 1 incorrect positive prediction, and correctly ruled out 56 cases. There were no cases where the model failed to identify a pituitary adenoma. Figure 8 shows that the model was able to fully transmit and decode the disease status in this category. It was able to correctly decode 97.9% of the illness status from the MRI data, and it did this with a 100% recall rate.

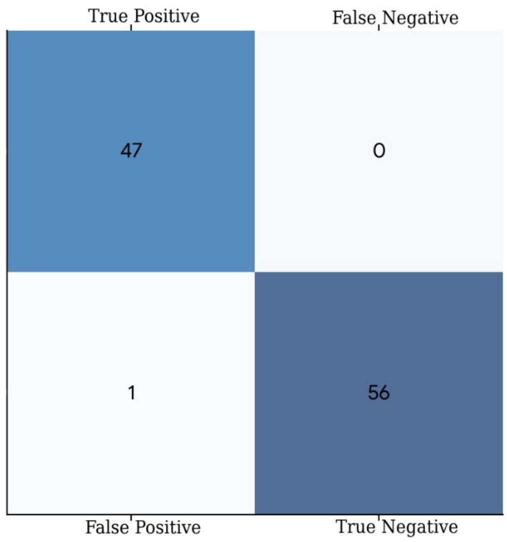

Figure 8. The Confusion Matrix for Pituitary Adenomas

The model for ependymomas has 41 true positives, 7 false positives, 4 false negatives, and 50 true negatives, yielding a precision of 85.4%. This indicates the possibility of enhancing the encoding and fine-tuning the encoding strategy. The recall rate of 91.1% indicates good decoding even in the presence of potentially noisy encoding (Figure 9).

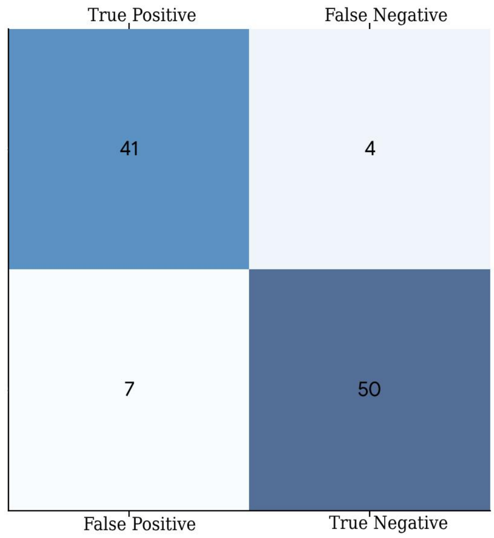

Figure 9. The Confusion Matrix for Ependymomas

The model's accuracy in identifying ependymoma is 85.4%, suggesting a somewhat high chance of false positives. To improve this, it is crucial to refine the encoding process to better differentiate authentic instances from individuals in excellent health. The model's recall rate is 91.1%, demonstrating a notably high degree of accuracy. This positive development ensures that individuals with the condition are less likely to be overlooked, therefore allowing for timely identification and treatment. The model has a good recall rate for capturing illness information but struggles to provide an accurate and distinguishing image of ependymoma, leading to false positive identifications.

The CNN model demonstrated great diagnosis accuracy across all illness categories, with sensitivity ranging from 81.6% to 100% and specificity from 80.2% to 100%. This successfully detected true positives and true negatives for dementia with Lewy bodies, large or giant aneurysms, and pituitary adenomas, achieving 100% sensitivity and specificity. The sensitivity for meningiomas was 81.6%, and the specificity was 80.2%. The model faced greater challenges with this particular illness category than with the others, leading to decreased ratings. The inadequate training data and the great visual resemblance between meningiomas and healthy scans may be the cause. Ependymomas had a sensitivity of 90.5% and a specificity of 88.3%. Additional training data and hyperparameter tuning could further enhance the model's performance on this disease. The diagnostic accuracy remained high throughout the 5 cross-validation folds, with small standard deviations. This indicates the model's robustness and ability to make reliable predictions on new test data. The CNN model accurately detects major neurological disease categories from MRI scans, validating deep learning as a promising technique for improving clinical diagnostics and workflow efficiency. Further research with larger datasets could help address performance gaps for challenging diseases such as meningiomas.

In this work, a study of patients with chronic diseases was conducted. However, the role of artificial intelligence has also been discussed for emergency conditions. Realizing the potential of machine learning in emergency care is a multifactorial task motivated by the potential for better and more effective patient care [19]. Thus, acute stroke caused by occlusion of large vessels requires urgent diagnosis and treatment. However, its radiological detection and the speed of medical care depend on many factors, including the experience of the doctor. Imaging software using artificial intelligence and machine learning is helping to accelerate the detection of strokes caused by large vessel occlusion [20].

The purpose of another review was to conduct a broad analysis of the capabilities of artificial intelligence in the context of neuroradiology. The latter is possible due to the implementation of an in-depth assessment and description of effective applications. In addition, a description of the potential impact of these components on neuroradiologists' tasks is a priority in this process [21].

The authors identified relevant applications, systematically collected and structured the information in a relational database, and coded the characteristics of the applications, their functionality for the radiology workflow, and their potential impact in terms of "support", "enhancement", and “substitution” of radiological tasks. 37 applications of artificial intelligence in the field of neuroradiology from 27 manufacturers were identified, which together offer 111 functions.

A large number of them allow radiologists to examine various types of tumor objects on images. Thus, the functions of artificial intelligence allow to increase the scope of capabilities of specialists, for example, by providing more data on pathological diseases. Smaller in scope is the category of functions aimed at partial or complete "replacement" of radiological tasks. The authors concluded that artificial intelligence in neuroradiology is emerging and developing, but can also be used in direct clinical practice. Most of the features have a positive effect on radiologists' productivity because they speed it up and improve quality. Certainly, there are no applications that can completely replace a radiologist in performing all his tasks and professional duties. However, some of them can contribute to increasing the efficiency of their work, performing a separate set of functions. The researchers also noted that scientific validation of AI-based products is more limited compared to other bodies [21].

Deciphering the huge number of components of electronic materials obtained at the expense of medical instruments during the years 2012-2022 can revolutionize modern medicine and create serious problems. Qualitative research allows modelling approaches to avoid or solve important problems. The technological development of society contributes to the hardware provision of fundamental changes in the processes of clinical machine learning [22]. The latter can be effectively used, while taking into account the specific manifestations of symptoms in patients [23].

It is important to note that the method of deep learning is already effectively used in various directions. For example, detection of Alzheimer's disease, description of acute neurological phenomena, segmentation of medical objects and mapping of connectomes. In addition, this methodological tool allows for the study of health disorders that belong to the system of autism or attention deficit hyperactivity disorder. It was possible to identify critical problems that arise in the process of integration and development of deep learning tools in parkit activities [23].

Artificial intelligence, including deep learning, is currently revolutionizing the field of medical imaging, with far-reaching implications for virtually all aspects of diagnostic imaging, including patient radiation safety [24]. There was also an emphasis on feedback between neuroscience and AI. The authors of one study [7] noted that the use of ideas obtained in scientific works on neuroscience will significantly improve the quality and speed of artificial intelligence evaluation. Thus, effective cooperation between artificial intelligence researchers and neuroscientists will reveal key issues that require immediate resolution. All this is possible due to the organization of empirical activity.

Based on the above, an important role in the development of neuroscience is played by communication between different specialists who can exchange knowledge and practices from different fields [25]. As a result, the development of artificial intelligence is expected, which will contribute to the deepening of a person's awareness of his own mind and thinking algorithms. The process of transforming intelligence into an algorithmic construct can reveal a number of unexplored facts in science about various components, including the human brain. The development and study of artificial intelligence will reveal some factors, such as creativity, the formation of dreams and even consciousness [11],[26].

In the current study, good results were obtained for the diagnosis of dementia with Lewy bodies. Despite the fact that modern diagnostic criteria for its detection use various biomarkers, the safety of the medial temporal lobe determined by the MRI procedure is characterized by low sensitivity. In addition, it has certain specificity, which as a result does not make it a priority, but only an auxiliary biomarker [27].

In a recent study, the authors studied how a deep learning approach could distinguish dementia with Lewy bodies from Alzheimer's disease using structural MRI data. For this purpose, two hundred and eight patients participated in a retrospective study. The architecture of a convolutional neural network of the residual neural network (ResNet) type, which is one of the deep learning models, was also used. Next, the classification efficiency achieved by the model was evaluated [28].

The authors of the described study obtained the following results: traditional statistical analysis identified no significant atrophy, except for subtle differences in the area of the middle temporal pole and hippocampus, at the same time, the function extracted by deep learning distinguished these two diseases with an accuracy of 79.15% compared to 68.41% when using the conventional method. The researchers came to the conclusion that by using a deep learning method with a demonstration of gray matter, specialists will be able to distinguish between diseases that are similar in structure, such as dementia with Lewy bodies and Alzheimer's disease. The priority of using such an approach is due to the fact that such subtle features may be underestimated by the traditional method [27].

Machine learning has also been used to diagnose other neurological pathologies, such as Parkinson's disease [29]. The authors of a paper on the study of machine learning for the diagnosis of pituitary tumors came to optimistic conclusions [30]. The essence of the scientific work was the formation and development of a specific model that would perform computer diagnostics using the neural system [31],[32]. For the purpose of scientific work, the indicators of adults by age of patients characterized by pituitary adenoma were taken. The control group consisted of individuals who do not have a pituitary adenoma. All collected post-MRI data was randomly divided into two categories, training and testing, 8:2 respectively. The direct diagnosis process was implemented based on the classification of various types of MR objects, based on the balanced voting approach.

The authors obtained the following results: the suggested method of a computer diagnostic system based on a convolutional neural network showed good diagnostic efficiency with an overall accuracy of 91.02%, sensitivity of 92.27%, specificity of 75.70%, positive prognostic value of 93.45% in certain types of MRI. In complex diagnostics, the method showed the best results with accuracy, sensitivity and specificity of 96.97%, 94.44% and 100%, respectively. The researchers concluded that the computer diagnostic system method they developed could accurately diagnose patients with pituitary tumors based on MRI images. In the future, the developers plan to improve this system by increasing the size of the dataset and evaluating its performance against an external dataset [30].

Previously, encouraging results were obtained from the use of AI in the diagnosis and treatment strategy of meningiomas [33]. Meningioma is a fairly common tumor among all primary tumors of the general nervous system. MRI is a standard radiological method for its preliminary diagnosis and monitoring. The growing volume of data highlights the potential of machine learning and radiomics in improving consistency and performance, and in providing new diagnostic, therapeutic and prognostic methods for neuro-oncological imaging [34].

Previously, the value of machine learning in the diagnosis of ependyma was also studied. The authors of a recent publication sought to distinguish between the signs of ependymoma and pilocytic. This task was accomplished through machine learning-powered radio microscopic analysis and description [35],[36],[37]. In the course of the study, 135 sections of magnetic resonance imaging were classified. To obtain 300 multimodal features, three forms of radio mics are used, namely Gabor transforms, texture warps, and wavelet transforms. The Kruskal Wallis test (KWT) and support vector machines (SVM) were used to classify different tumor types. In order to establish and evaluate the performance, an analysis of various properties of the receiver (AUC - Area Under Curve) was carried out [38].

As a result, the following indicators were obtained: 0.8775, 0.9292, 0.8000 and 0.8646. The first reveals the accuracy, the second the sensitivity, the next the specificity, and the last the AUC. Textural features are the most effective, as they ensure high quality of the differentiation process, which allows for consistent results. Based on this, it can be established that it is the textural functions that play a more important role, unlike the others [39],[40]. Modern radiomics implemented on the basis of machine learning is effective for differentiating tumors of the posterior cranial fossa in children and can improve the use of radiomics methods for auxiliary clinical diagnostics [41].

The use of a separate model of computer diagnostics was successful. Its nature comes from the foundations of artificial intelligence, as well as the neural system, which allows the detection and evaluation of cerebral aneurysms that do not explode. In addition, these indicators were considered in experimental forms. It is worth noting that there is no unanimous position regarding the possibility of qualitative detection and research of such aneurysms in practical clinical activity. For example, in one scientific work, the diagnostic functions of computer diagnostic models were investigated. This allows such systems to be used to classify cerebral aneurysms into different types [42].

Unlike the current study, which identified large (16-25 mm) and giant (greater than 25 mm) brain aneurysms, the system of the aforementioned work could detect critically small aneurysms that are located between arteries that radiologists cannot locate and evaluate. It was also noted that in the future this method may have both advantages and disadvantages. The first includes a significant reduction in the workload of specialists, in particular radiologists, as well as diagnosticians. The disadvantage of this approach is the reduction of the cost and value of human labor [42]. Attention was also focused on the possibility of replacing doctors with a neural network and on aspects of artificial intelligence in clinical practice as assistants to doctors [43],[44]. AI has improved clinical diagnosis and decision-making efficiency in several areas of medical tasks [45].

The purpose of another article was to give an idea of the current possibilities of using AI in neurosurgery. Its authors conducted a literature review with an emphasis on illustrative works on the use of AI in neurosurgery. Current publications on the use of AI show a variety of topics in this area. The main areas of application are diagnostics, models of outcomes and treatment. The authors concluded that various applications of AI in the field of neurosurgery with improved preoperative diagnosis and prediction of outcomes will significantly affect the future of neurosurgery. Neurosurgeons will continue to make decisions about indications for surgery, but in the coming years, with the help of artificial intelligence, neurosurgeons will make an optimized statement about the diagnosis, treatment options and risk of surgery [46].

Many studies have been published on the use of AI in neuroradiology, and this trend is picking up the pace. A wide range of such instruments are actively used in practical clinical activity. For example, automatic detection of ASPECTS, investigation of intracranial hemorrhages and evaluation of compression injuries of vertebrae [47]. A wide range of medical indicators remained unexplored, which may be objects of scientific research in the future. Among them, finding the genome of a glioma, diagnosing a stroke or multiple sclerosis [48]. The application of machine learning methods to neuroimaging has grown faster than could have been predicted 15 years ago. This direction has expanded the field from population analysis to individual biomarkers of diseases or functional states of the brain. From a clinical standpoint, this extension is obviously of fundamental importance for the diagnosis, prognosis and stratification of patients. Although small studies will continue to be published and open up new horizons, the results should always be presented and received with caution until they are replicated in larger studies [49],[50],[51].

Machine learning offers one of the most interesting directions in the field of neuroimaging, since it is directly related to accurate diagnosis in clinical neuroscience and identification of various brain states in cognitive neuroscience [52],[53]. Thus, artificial intelligence and machine learning in neurosurgery are becoming increasingly important as technology advances. [54] has illustrated that such development in AI technology could be beneficial to social development. This development can be seen in the increase in publications on AI in neurosurgery in recent years and the breadth of issues covered.

5. Conclusion and Future Works

In this study, a convolutional neural network (CNN) model was developed for the automated diagnosis of neurological diseases from MRI scans. The CNN architecture extracted hierarchical feature representations from the image data through convolutional and pooling layers. These features were used by fully connected layers to perform multi-class classification between healthy scans and major disease types. The CNN model showed high diagnosis accuracy, with sensitivity ranging from 81.6% to 100% and specificity ranging from 80.2% to 100% for different illness categories. The detection of dementia with Lewy bodies, massive aneurysms, and pituitary adenomas was accurate. The model struggled to recognise meningiomas due to its poor accuracy. This showed excellent sensitivity in recognising ependymomas but had reduced specificity, suggesting a risk of false positives. Additional training data and hyperparameter adjustments may help to improve the performance of diagnosing ependymomas. It's important to look at bigger data sets to make the results more general, to see how different treatments work for complicated conditions like meningiomas, and to think about using advanced deep learning techniques or model design.

In general, the CNN model provides a promising approach to aid healthcare professionals in accurately diagnosing neurological diseases from MRI scans. Further research should focus on improving AI techniques, increasing databases, involving more patients for each of the diseases, including a larger control group. Attention should also be focused on hanging the performance and strength of artificial intelligence. Future collaborative efforts may eliminate some limitations in available research resources to take advantage of the expanded and evolving capabilities of machine learning approaches in the healthcare system.

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