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Neural Networks In Medical Neuroimaging: Advancing Detection And Treatment Of Neurological Disorders And Brain Tumors

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ABSTRACT

Objective: This paper aims to evaluate the role and performance of Neural Networks (NNs) in medical imaging of neurological disorders such as Alzheimer's disease, Parkinson's disease, stroke, brain tumors, and Multiple Sclerosis. To that end, the study seeks to assess the effectiveness of AI-assisted NNs in enhancing disease accuracy, ease, and treatment outcomes, in addition to unraveling constraints to utilizing such innovation in healthcare facilities.**Methods:** A convenient sample of 250 healthcare professionals from the subsets of radiologists, neurologists, developers of AI, and healthcare administrators were targeted. The structured questionnaire used quantitative data to gather information on how familiar the respondents are with NNs, how often they use them, and their perception of the concept. Descriptive analysis, reliability analysis (Cronbach's Alpha), normality analysis (Anderson-Darling), and correlation analysis (Pearson's r) were used to analyze significant variables, including familiarity, perceived effectiveness, and likelihood to recommend.**Results:** The findings indicate that participants are moderately familiar with NNs, where usage differs across neurological disorders. Alzheimer's disease and stroke were identified as the two diseases in which NNs were most beneficial; however, usefulness was low for other diseases such as Parkinson's disease and Multiple Sclerosis. When performing the reliability test, it obtained a low Cronbach's Alpha, which suggests that there is a weak internal consistency between measured items. Moreover, there was low interaction between the level of familiarity, perceived effectiveness, and likelihood of recommending AI technologies, which indicated that different professions may have different beliefs about AI technologies. Challenges that limited the adoption of the models were costly, lack of explanation, and sheer legal issues.

Conclusion: There are opportunities for using NNs in medical imaging of neurological disorders and their treatment, which have significant uses in Alzheimer's and stroke. But, for the most part, using the technologies mentioned earlier largely remains limited due to financial constraints, technological limitations, and existing regulations. More development is still required regarding AI transparency, training, and affordable application to improve the confidence and frequency of use by the large spectrum of healthcare workers. There are also areas for future research: first, the use of AI in less researched neurological disorders; second, increasing the robustness of the AI models and the readability of the results.

Keywords: *Artificial NNs, magnetic resonance imaging, application of artificial intelligence in medicine, neurology, Alzheimer's disease, apoplexy, machine learning, diagnostic performance, health informatics.*

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1. INTRODUCTION

Artificial intelligence (AI) mainly relies on Neural Networks (NNs) as one of the chief techniques, and it has become an innovative technology in the healthcare field, especially in medical imaging. NNs have most recently been integrated into diagnostics as well as neurologic disorder management because of their intriguing possibility to advance exact diagnoses as well as treatment results. Alzheimer's disease; Parkinson's disease; stroke; tumors; multiple Sclerosis; and neurological disorders; are detected and monitored with MRI, CT, and PET imaging technology. But interpretation of images by human experts has some in-built drawbacks and limitations. Standard deviations, errors from different human factors, and time-consuming diagnostic tests hinder the early treatment of complex conditions, which may impact the outcomes of the patients (Khalighi et al., 2024) (Noor, Zenia, Kaiser, Mamun, & Mahmud, 2020).

Hence, applications of NNs particularly convolutional NNs (CNNs) have displayed promising results in tackling these challenges. These models are developed to identify patterns from big data sets and hence are capable of analyzing complex medical images with precise measures of accuracy. NNs can identify involutional changes in the structure of the brain, analyze disorders in the imaging data, and distinguish between various neurological diseases with a diagnostic accuracy that can exceed conventional methods for diagnostics. For example, in Alzheimer's disease, a first-line diagnosis through imaging technique is very vital to delay the disease's progression. The suggested paper proves that the application of the NNs allows identifying early signs of Alzheimer's, which can be missed even by humans analyzing the radiological images of brain tissue (Gautam & Sharma, 2020; I. Hussain & Nazir, 2024b).

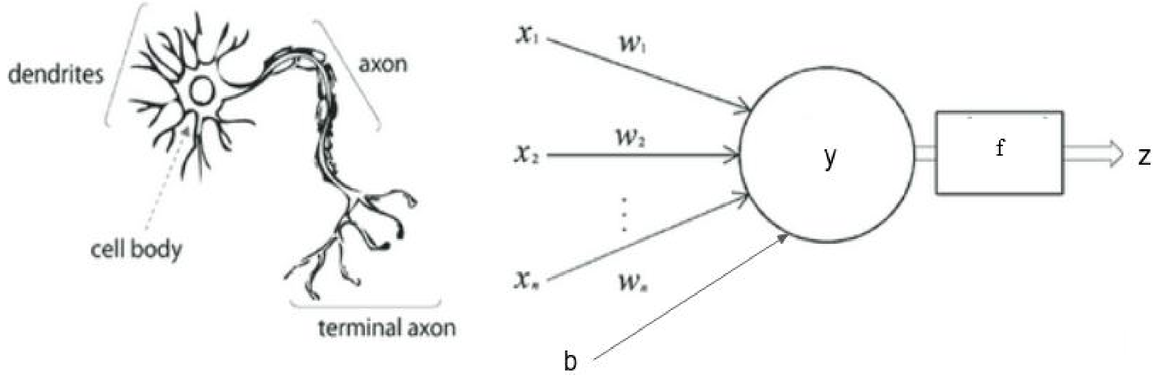
Nevertheless, their use in clinical practice has been more evolutionary as pointed out below. As the use of AI continues to trend towards the incorporation of healthcare, some challenges persist. However, they hold a big disadvantage – one of them is that NNs are a so-called 'black box'. Such models frequently give very accurate results although people cannot understand how they arrived at their conclusion. This lack of transparency makes clinicians reluctant to rely on the accuracy of the algorithms and that is especially so when the diagnostic involves neurological conditions. In addition, the integration of NNs in clinical environments can be expensive. Creating, uplifting, and sustaining these sorts of artificial intelligence systems requires substantial and diverse amounts of data, calculation power, and specialized staff that may not be readily available in all hospitals or related healthcare facilities (Daidone, Ferrantelli, & Tuttolomondo, 2024; Yu, Yang, Zhang, Armstrong, & Deen, 2021).

However, the constraints posed by regulations and potential bias in models create extra challenges. NNs are said to be data-oriented and the performance decision depends on the type and amount of data set they are fed with. This now means that if the training data is not a good sample representation of the patient population, then the models used will also be prejudiced and this would further lead to prejudiced results. This is even worrisome in neurological disorders due to the inconsistency and mechanisms of damage to different structures and corresponding symptoms in different people. Therefore, the preparation of more general, informative sets for training the NNs is an important prerequisite for applying the concept of artificial intelligence in clinical practices (Ahsan, Khan, Khan, Sinha, & Sharma, 2024; Raghavendra, Acharya, & Adeli, 2020).

However, the incorporation of NNs in medical imaging remains an area of development, and there have been important developments in the diagnostic procedure of some neurological conditions. Indeed, NNs exhibit high performance in the diagnosis of stroke, brain tumor, and Alzheimer's disease since they can quickly analyze vast amounts of imaging data compared to radiologists' approach. For instance, the application of artificial intelligence to identify strokes has benefits in reducing the time to make the diagnosis, which is critical to improving the chances of limiting the damage experienced by stroke patients. Likewise, NNs are being applied for the classification of tumors in the brain, distinguishing between primary benign and secondary malignant growths with good outcomes. This research seeks to identify the current state, perceived effectiveness, usage, and characteristics of NNs in medical imaging for Neurological disorders, and the potential challenges that discourage their widespread use (Du et al., 2024; Patel et al., 2021).

2. NNS AND CNNS

The basic unit of a NN is a neuron, which can receive inputs and return the corresponding output. A biological vs classic artificial neuron is described as follows with zero bias.



Where x_1,...,$x_n$are the inputs, w_1,...,w_n the corresponding weights and b as bias.

- **Forward calculation:** When these components are received, then $y = \sum_{i=1}^{n} \quad x_i w_i + b$ passes through f and the neuron returns $\hat{y} = z = f(y)$.
- f represents the neuron activation function that maps a real number to a number between 0 meaning deactivated and 1 meaning fully activated.

The classical form of f is 1 if $y \geq 0$, 0 otherwise, and this concerns the earliest unit of NN, namely the perceptron, but this can only classify data that could be separated by a straight line or hyperplane.

As for the neuron, the most known forms of f are $\frac{1}{1+e^{-x}}$ (sigmoid), $\frac{e^x - e^{-x}}{e^x + e^{-x}}$ (tanh), 0 if $x \leq 0$, x if $x > 0$ (rectified linear unit or simply $max(x, 0)$), x if $x \geq 0$, $a.x$ otherwise (leaky rectified linear unit) with a sufficiently small constant between 0 and 1.

- **Back propagation**: During NN training, a back calculation through the gradient descent optimizes the parameters. For example, suppose we aim to have some z_0 for the output z. The approximation will be made through the adjustment of parameters w_1,...,w_n, b.

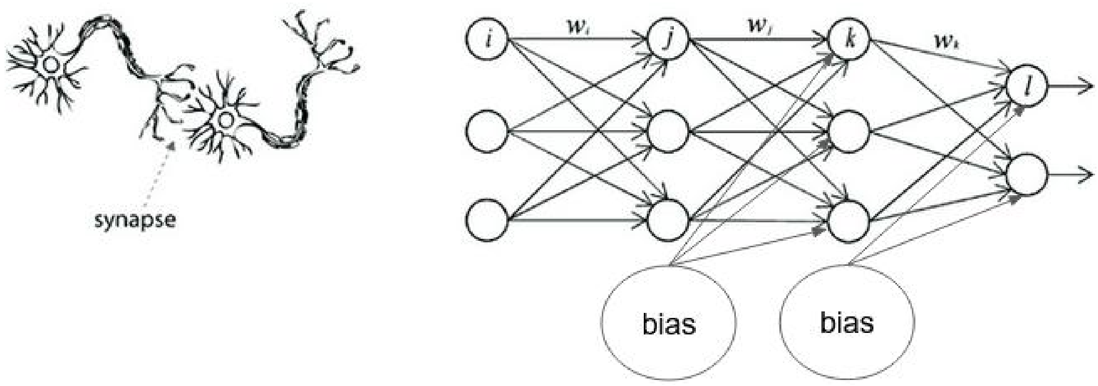
The two derivatives $\frac{\partial z}{\partial w_i}$ and $\frac{\partial z}{\partial b}$ are:

$\frac{\partial z}{\partial y}\frac{\partial y}{\partial w_i} = \frac{\partial f(y)}{\partial y} x_i$ and $\frac{\partial z}{\partial y}\frac{\partial y}{\partial b} = \frac{\partial f(y)}{\partial y}$.

By using a learning rate η, the update will be made through:

$\Delta w_i = \eta(z_0 - z)\frac{\partial z}{\partial w_i}$ and $\Delta b = \eta(z_0 - z)\frac{\partial z}{\partial b}$.

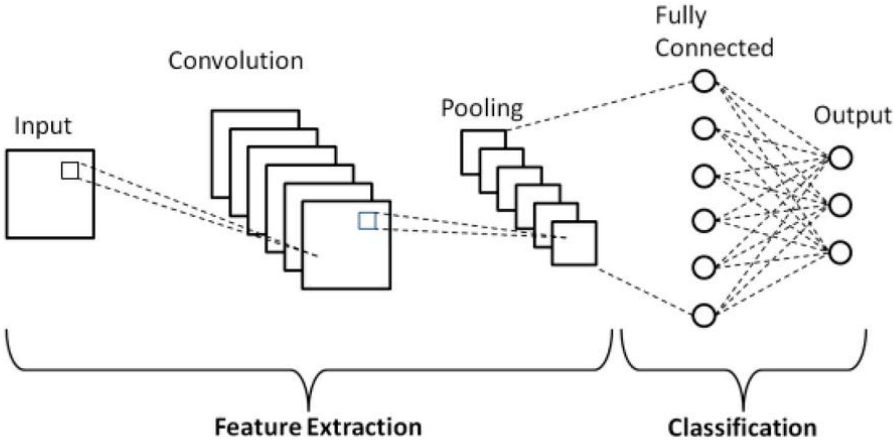
One of the most significant models in machine learning is the NN. The structure of biological NNs is very similar to that of artificial NNs, which are made up of many neurons connected to one another as presented below.



Compared to neurons, NNs can learn complex relationships in data due to its multiple hidden orange layers.

The way an NN learns is as follows: Starting with random weights or values, the back propagation algorithm iteratively updates the weights or values of the connections between neurons until the model operates fairly accurately. Ultimately, an NN''s learned information is digitally stored in its connections. The majority of neural network research attempts to alter the model's learning process (using different structures or algorithms) in an effort to increase the model's capacity for generalization.

CNNs have several layers as described in the following illustration and explained below.



- **Convolution layer:** To find patterns and extract features, the convolution layer applies a set of filters as matrices of weights to the input image. The number of pixels the filter moves in each step, defines how the filter moves across the image. By adding extra pixels around the input, padding can occasionally be used to adjust the output size. Valid, zero padding (no padding), same padding (output size equals input size), and full padding (increases output size) are the various forms of padding. The $\boldsymbol{f}$ function as shown above, especially the rectified one, is applied after the convolution operation.
- **Pooling layer:** It maintains the most significant features, in order to reduce the computing complexity.
- **Fully connected layer:** It classifies the output by using the high-level features learned by the convolutional layers to perform the final classification or regression task.

3. NEUROIMAGING AND CNNS

CNN models in neuroimaging, may help in classification tasks by implementing them in most-known techniques in this regard, namely Positron emission tomography (PET), Single-Photon Emission Computed Tomography (SPECT), Electroencephalogram (EEG), Magnetoencephalography (MEG), functional Near-Infrared Spectroscopy (fNIRS) and Functional Magnetic Resonance Imaging (fMRI). As examples, some authors explored the result from CNNs for PET classification to predict Alzheimer disease and recommended that additional investigations are needed on other datasets while concluding that the development of deep learning in this context may improve this research more in the future (Khagi & Kwon, 2020). Other researchers proposed a CNN-based model to classify Parkinson disease patients while relying on SPECT data (Hathaliya et al., 2022). There is also a study where the authors evaluated a CNN-gated recurrent unit-attention mechanism method to detect and predict epileptic seizure in pediatric patients and their results validated the effectiveness of their model to identify the state of EEG signals (Zhang et al., 2024). In another study, some researchers presented a novel CNN system to decode MEG recordings and predict early signs of Alzheimer disease. By using another CNN method, some authors succeeded to improve the classification of the signals of fNIRS-based brain-computer interface (Shi et al., 2024). As a final example in this part, other researchers tried to assist in the screening of schizophrenia through the combination of CNNs and fMRI (Qureshi et al., 2019).

4. AIMS AND OBJECTIVES

This research aims to gather information on how these technologies are currently employed in practice by conducting surveys of healthcare workers, including radiologists, neurologists, and AI developers and researchers. It will be necessary to identify how such NNs influence diagnostic precision, speed, and outcomes for patient care to know how to progress new AI-assisted, knowledge-based tethered consciousness treatments and interface phenomena in the subsequent years to the obsolescing, often ineffective and nebulously evidenced, conventional treatment standards amid the escalating global neurological disease burden. The significance of NNs increases as they develop; to transform the area of neurological diagnosis and treatment, these tasks require the subsequent development of AI technologies, and their ability to be trusted, explainable, and utilized by healthcare professionals (Abhisheka, Biswas, Purkayastha, Das, & Escargueil, 2024; Kim et al., 2019).

AI in particular NNs has been one of the most researched areas in the healthcare sector in the last decade. However, there has been a tremendous innovation with the introduction of NNs or incorporation in medical imaging which has a possibility of enhancing the base or the ground of superior diagnosis of different ailments, particularly neurological diseases. This part of the paper provides a literature review of the current work done in deploying NNs in medical image analysis for diagnosing neurological disorders including Alzheimer's disease, Parkinson's, stroke, brain tumor, and Multiple Sclerosis (Suryadevara & Yanamala, 2020; Voigtlaender et al., 2024).

This is especially true for the deep learning models which were singled out as the most efficient for image analysis. Probably, the most popular model used for medical imaging in deep learning frameworks is Convolutional NNs (CNNs) in hierarchical deep learning systems since they can efficiently manage big volumes of complicated image data and autonomously assess them for feature patterns devoid of feature engineering. CNNs for instance, as the authors Litjens et al., reveal, has impacted the field of medical imaging from disease identification to outcome identification based on imaging data. Still, the main strength of CNNs is in pixel-level feature extraction which makes them relevant to such applications as tumor segmentation, lesion detection, and organ classification (Haque, Hassan, Bairagi, & Shariful Islam, 2024) (Valliani, Ranti, & Oermann, 2019).

Unfortunately, in neurological disorders, the beginning of the disease is often marked by diagnostic imaging which is vital in treatment. Research has shown that CNNs can indeed pick out small differences in the chemical makeup of the brain that should be evident from neurodegenerative diseases before the symptoms appear. Such detection of early signs or symptoms of diseases such as Alzheimer's and Parkinson's can greatly enhance patient care since early diagnosis is usually possible (I. Hussain & Nazir, 2024a; Khan et al., 2021).

5. ALZHEIMER'S DISEASE DETECTION

Alzheimer's disease is amongst the most common neurodegenerative diseases worldwide and it is important to diagnose them early to try to delay the development of the disease in the affected individuals. Current diagnostic techniques rely on the subjectivity of radiology skills which may differ from one practitioner to the other and are very time-consuming. Recent developments in the field of artificial intelligence, specifically CNNs have shown the potential to automate solutions for MRI and PET images of initial symptoms of Alzheimer's disease. The accumulated results show values above 90% of diagnostic accuracy, Suk et al evidence that CNN models outcompete other conventional techniques in detecting AD-related changes in brain structure (Ibrahim & Mohammed, 2024; Kalusivalingam, Sharma, Patel, & Singh, 2021).

In addition, the identification of patient subtypes with MCI has been a significant focus of investigation because MCI has been determined to be a precursor to Alzheimer's disease. Research has shown that CNNs can accurately forecast the transformation of MCI to AD by distinguishing the tiny variations in brain structure. This capability will be helpful mostly in the early phases of MCI and treatment planning to better control the potential development of AD (D. Pan et al., 2020; Zhan et al., 2024).

6. STROKE DETECTION AND CLASSIFICATION

Stroke is a condition that leads to both death and disability and can be fatal if not diagnosed in the right time to prevent complications. Artificial NNs can provide automated detection and classification of the stroke from images and more specifically differentiate between Ischemic and Hemorrhagic stroke. Several researches have been based on the use of CNNs in CT and MRI scans to quickly identify the occurrence of a stroke as well as the extent of the brain damage (I. Hussain & Nazir, 2024c) (Sankareswaran & Krishnan, 2022).

Kam et al. noted that NNs could also classify CT signs' potential to show acute stroke with high levels of effectiveness as that of radiologists. Probably the greatest strength of AI in stroke detection is its rapidity, which is especially pertinent in strokes where; every hour that passes without sufficient intervention is detrimental. CNNs have also been used for prognostication of patient outcomes depending on the first scan, and make the best decision regarding future management, including thrombolysis or mechanical thrombectomy option (Dhankhar et al., 2024; Liu et al., 2019).

1. Brain Tumor Classification

Another example is also possible with brain tumors as one of the successful applications of NNs. Conventional diagnosis of brain tumors involves macroscopic evaluation of the tumors and grouping the tumors based on the characteristics that are observed in MRI or CT images. This process is both time-consuming and involves higher inter-observer variability. Try as it might, performing this task manually can be tedious and most of the time not very accurate; however, this is where CNN-based models come in handy by performing this task automatically. A recent study by authors Pereira et al. 2016 shows that CNN can accurately differentiate between different types of tumors including gliomas, meningiomas, pituitary tumors, and so on (Aljahdali et al., 2024; Hu, Zhong, Xie, Lv, & Lv, 2021).

These models not only enhance the diagnostic speed but also make a crucial differential view of the tumor which is significant from the therapeutic viewpoint. Other works have approved the application of NNs to predict tumor grades that control the therapeutic plans and prognosis. For instance, CNNs have been used to improve the evaluation of low-grade gliomas from high-grade gliomas – a feature that is very helpful in choosing therapy for glioma surgery (Malhotra, Gupta, Koundal, Zaguia, & Enbeyle, 2022; Nazir & Hussain, 2024a).

7. MULTIPLE SCLEROSIS DETECTION AND MONITORING

Multiple Sclerosis is an inflammatory demyelinating disease of the central nervous system that results from the formation of plaques in the brain and spinal cord. MRI is the most widely used imaging modality to detect and assess the evolution of MS. However, lesion detection and segmentation from MRI scans may be ambiguous due to the inhomogeneous size and density of lessons and manual segmentation is a time-consuming process, in addition to the variability that may arise due to different observers (Arabahmadi, Farahbakhsh, & Rezazadeh, 2022; Saleem et al., 2024).

Automated segmentation of MS lesions has been performed with the use of NNs making this process more accurate and faster. According to Valverde et al., CNN has been widely used and has considerable abilities to demonstrate high accuracy for detecting the lesions of MS in MRI, compared with the conventional ML methods. These models can follow the lesion changes over time and give very important information about the efficiency of the treatment and development of the sickness (Henry & Jonathan, 2024; S. Hussain et al., 2022).

8. CHALLENGES AND POSSIBLE BENEFITS

However, several issues limit the application of NNs to medical imaging though they have shown great promise in diagnostics and diagnosis. This paper identifies one of the main challenges facing the utilization of these models as being the problem of interpretability, also known as the 'black-box' issue. When clinicians make a decision based on the results created by the AI they may not know how the NN came to the current decision. In line with what Tjoa and Guan pointed out in their paper published in 2020, it is imperative to work on a high level of explainability so that members of the medical professions can trust an AI. Research is being conducted with the view to creating new forms of NNs that can elaborate ways of generating more comprehensible decision-making mechanisms, which could improve the understanding and acceptance of clinicians (Taciuc et al., 2024; Yadav & Jadhav, 2019).

Another challenge is that NNs are sensitive to the profiles and size of data sets that are fed to the NNs. In the case of many NNs in healthcare, the models' data are derived from a few sources and may not be representative of patients of different populations. Prejudice in Artificial intelligence-modeled systems has been reported and tends to increase health disparity if unchecked. The failure of NNs to operate optimally in certain demographics is mostly attributed to the underlying dataset and this motivates endeavors aimed at creating improved datasets that are diverse (Keles, Keles, Keles, & Okatan, 2024; Wong et al., 2023).

NNs are also costly, and this has remained a hurdle when it comes to implementing such systems in healthcare settings. AI work is not cheap, as it demands a huge amount of investment to design, install, and maintain the applied systems and to attract and employ the required specialists. The transition to these technologies may therefore not be easy for small healthcare institutions because of the costs involved, according to He et al. However, the costs such as the machinery, skilled labor, knowledge, and even the time required to implement this type of technology may become cheaper over time as more people embrace it (Ramzan et al., 2020; Sachidananda Murthy & Prasad, 2024).

NNs for medical imaging seem to be bright with current research being driven mainly by the desire to enhance the efficiency, reliability, and versatility of such models. Future development of AI technology raises the possibility of moving applications of NNs to other aspects of clinical practice like treatment or individualized medicine. Incorporating artificial NN results with data from genetics and clinical information may enhance the benefit of patients with neurological diseases (El-Assy, Amer, Ibrahim, & Mohamed, 2024; Ozturk et al., 2020).

9. METHODOLOGY, DATA COLLECTION AND ETHICS

This research work adopts the research paradigm that utilizes quantitative data in analyzing the effects as well as the efficacy of NNs in healthcare with special reference to neurological imaging for the diagnosis and management of neurological diseases. The purpose of this study is to determine the application of artificial intelligence-powered NNs in enhancing diagnostic performance, effectiveness, and treatment planning in instances of Alzheimer's disease, Parkinson's disease, stroke, multiple Sclerosis, tumors, and much more. Through surveying a group of structured questions from qualified specialists working with medical imaging and AI this study seeks to substantiate practical experience and potential developments in the application of NNs within the healthcare field (Dodda, Chintala, Kanungo, Adedoja, & Sharma, 2024; Lamrani, Cherradi, El Gannour, Bouqentar, & Bahatti, 2022).

In the current study, the research design employed is the cross-sectional survey because of its efficiency in the collection of quantitative data during a given period. A structured questionnaire will be completed by healthcare professionals including radiologists, neurologists, AI researchers, biomedical engineers, and healthcare administrators. This approach allows the research to accumulate a vast amount of data in a short time and at the same time, captures variations in professionals' attitudes and experiences with or without direct contact with AI in medical imaging (Ali et al., 2024; Ashraf, Qingjie, Bangyal, & Iqbal, 2023).

This research therefore used purposive sampling and convenience sampling. Quota sampling guarantees that only the respondents who possess adequate relevant experience in either medical imaging or NN applications are selected. Convenience sampling is advantageously used herein to include study participants who are available and willing to offer their samples and time towards the study within the stipulated time. The target sample is to have a total of 250 respondents considered enough for survey analysis and generalization of the findings based on the nature of this research (Aggarwal, Saini, & Gupta, 2024) (Mehmood, Maqsood, Bashir, & Shuyuan, 2020).

For this purpose, participants were given a structured questionnaire developed for this particular study where quantitative data concerning the application of NNs for medical imaging of neurological disorders can be obtained easily. Respons will be able to choose from multiple options to several questions; the others will imply the use of the Likert scale to find out the frequency of the AI tools usage, the familiarity of respondents with the NNs, and the efficacy of the AI technologies versus conventional diagnostic approaches (Khalifa & Albadawy, 2024; Salahuddin, Woodruff, Chatterjee, & Lambin, 2022).

The questionnaire have been divided into several key sections:

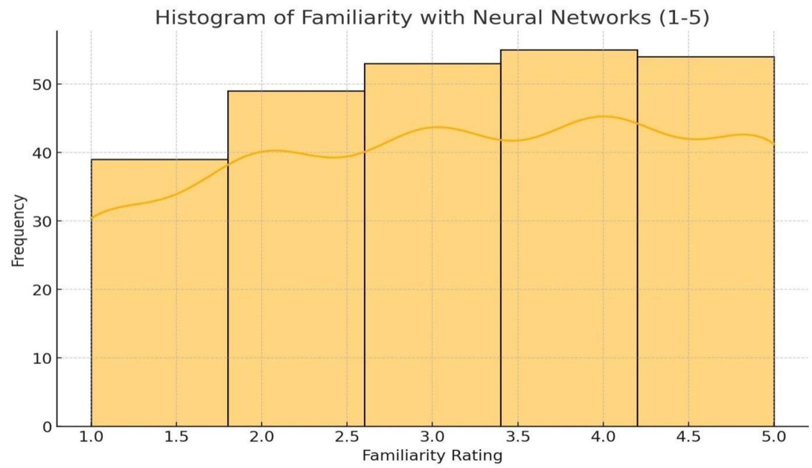
- Demographics: The section of this study will comprise of age, gender, occupation, and years of experience of the respondents. This information will serve as an important basis for researching the correlation between demographic respondent profiles and respondent NN perception (Nazir & Hussain, 2024b).
- Familiarity and Usage: From the questionnaires, subjects were questioned about their level of awareness of NNs in medical imaging, the frequency of using AI-based diagnosis, and for what neurological disorders they get the most out of NNs. The answers to these questions allow us to determine the level of working with NNs for representatives of various industries and professions (Das & Goswami, 2024).
- Effectiveness and Efficiency: On this basis, this part will discuss whether the diagnoses based on the aid of NNs are accurate and fast enough. By using a scale similar to the one below, respondents will be asked to compare a NN with conventional diagnostic procedures concerning the diagnostic accuracy and time that is being saved during the diagnostic process. Other questions refined the extent to which the utilization of NNs minimizes the human factor and optimizes treatment strategy (Das & Goswami, 2024).
- Barriers and Adoption: To get the data about the existing limitations WirelessIDIOT respondents will be asked about difficulties in usage such as high costs, lack of interpretability, regulatory measures, and bias in the AI models. This section will also include additional variables on how far implemented in various healthcare establishments and whether the respondents think that NNs were the dominant method of diagnosing neurologic disorders in the future (Sellappan, Pershiy, Shadrach, Balasamy, & Renu, 2024).
- Future Prospects: The last questions of the survey will assess the respondents' beliefs regarding the application of NNs in healthcare, as well as the necessary investments, and enhancements to the existing AI systems (Etekochay et al., 2024).

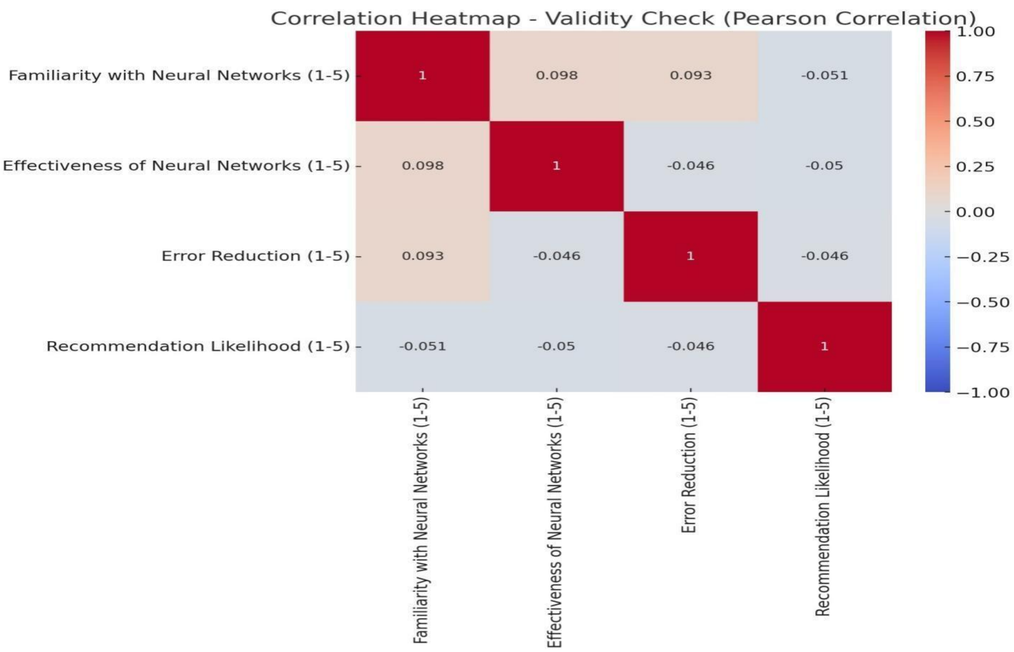
When data is collected then it will be analyzed with the help of descriptive analysis as well as inferential analysis. Measured descriptive statistics will be mean, median, mode, and standard deviation in that the study seeks to establish the centrality and variability of the data set. This will afford a general picture of the respondents' preferences and encounters with NNs. Analytical methods will be employed to help with finding the directionality between two or more variables. For instance, one might decide to use an independent sample t-check to establish if there is a significant difference in the gender of respondents who rate NNs high, and those who do not (Al-Kadi et al., 2024).

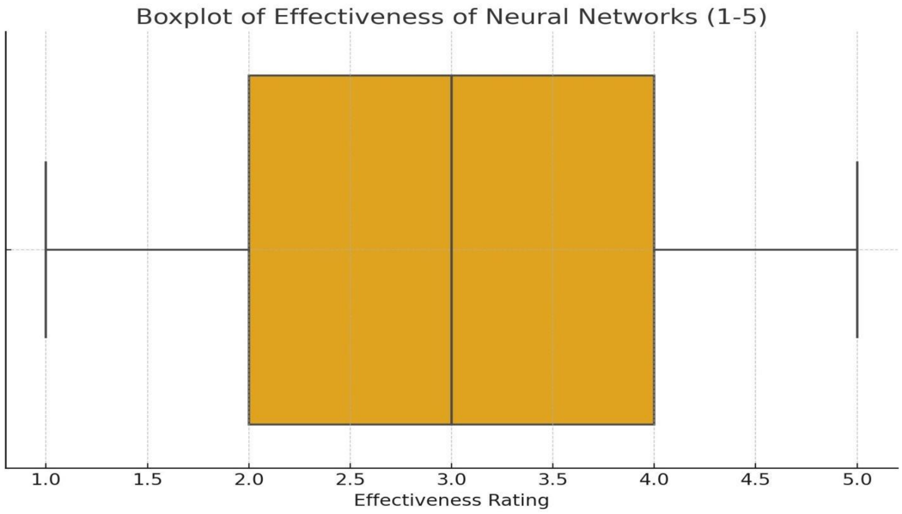
Likewise, t-tests could be used to compare responses across groups; for instance, radiologists and AI technophobes; or institutions that have fully integrated NNs and centers that are still deliberating on whether to integrate them. The use of inferential purposes is that conclusions about the factors that improve outcomes, the factors that enhance adoption, and the factors that show the potential of NNs in medical imaging are epic (Galić, Stojanović, & Čajić, 2024; Williams, 2024).

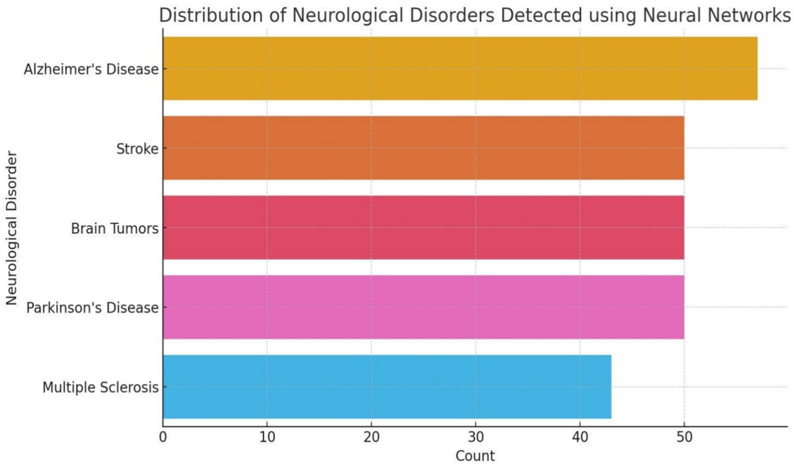
Issues of ethics shall be upheld throughout the study. The survey will be conducted anonymously and without the involvement of the respondents' identities, so participation will be voluntary. Participant information and consent will be sought from all participants, and they shall be allowed to opt out of the study at any time. Moreover, the respondent's personal information and other data that may be deemed sensitive will not be required except for the demographic data used in the analysis. The study will also ensure that the survey is completed within a reasonable time and independent of the participant's work calendar .

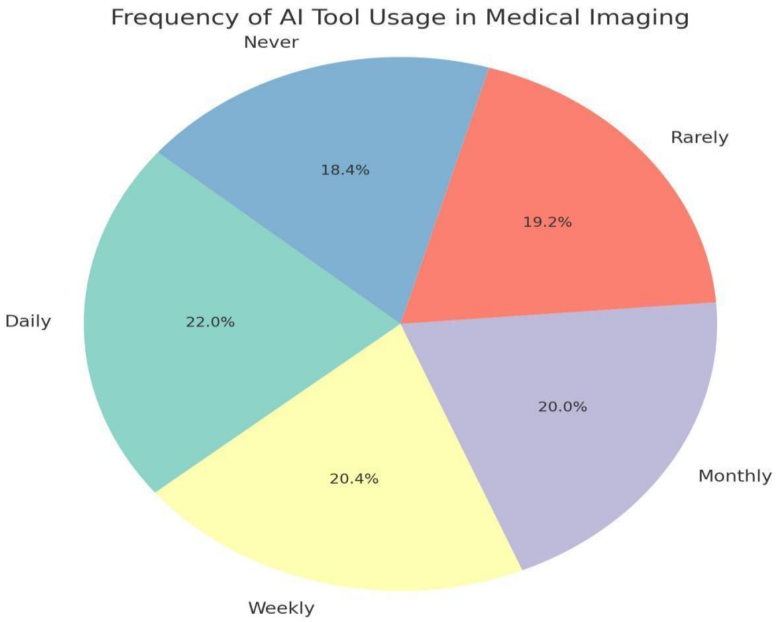
10. DATA ANALYSIS

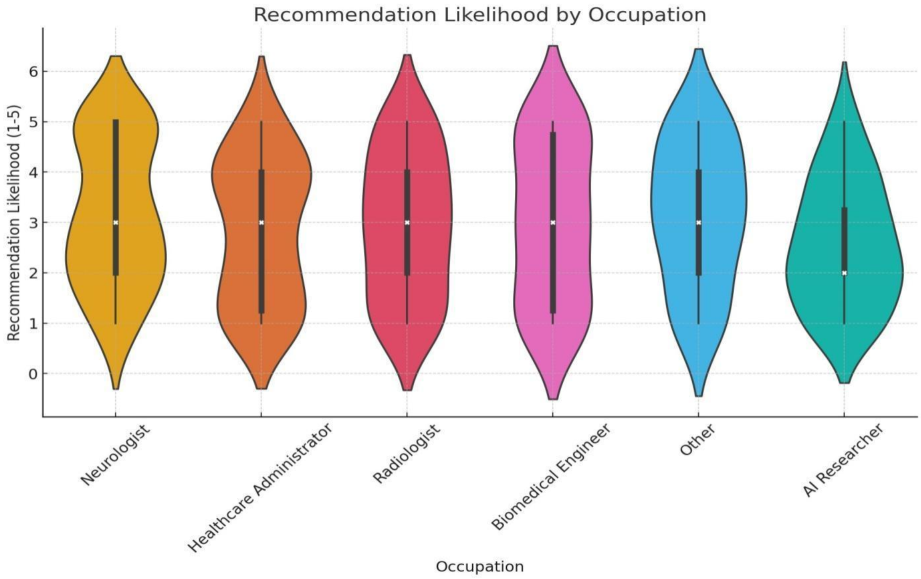





Boxplot of Effectiveness of Neural Networks (1-5)
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
Effectiveness Rating


Distribution of Neurological Disorders Detected using Neural Networks
Alzheimer's Disease
Stroke
Brain Tumors
Parkinson's Disease
Multiple Sclerosis
Neurological Disorder
0
10
20
30
40
50
Count


Frequency of AI Tool Usage in Medical Imaging
Never
18.4%
Rarely
19.2%
Daily
22.0%
20.0%
Monthly
20.4%
Weekly



Interpretation of the Tests and Charts

Normality Test

Based on the normality test whose result is shown in the table below and was ascertained using the Anderson-Darling test, most of the numerical variables are not normally distributed they include; This is a result of the high test statistics and very low p-values well below the 0.05 test level, this however means that the data is non-normally distributed. This may mean that the responses are not completely representative, maybe due to variations in the understanding of and contact with NNs among the participants (Siuly, Khare, Kabir, Sadiq, & Wang, 2024).

Inter-Item Reliability Test: Cronbach Alpha

Cronbach's Alpha scale for the Likert-type response is 0.003, this is very low which means that there is very poor internal reliability for the items: Familiarity, Effectiveness, Error reduction, and Recommendation likelihood. This makes a discouraging suggestion that these questions simply do not measure the identical underlying construct in a way that is all that dependable. The low alpha could also mean that participants' experiences and perceptions of the NNs differed greatly as could not establish a pattern as seen on these items (Kadhim, Mohamed, Najjar, & Salman, 2024).

The Pearson Correlation Coefficient Test or also known as the Validity Test.

As revealed through the Pearson correlation test, there is a low correlation between the most important variables. For example, the relationship between "Familiarity with NNs" to "Effectiveness" is computed to be a modest positive correlation that equals 0.097, which is also an insignificant result since the p-value is equal to 0.123. It is also important to note from Table Five that both the relationships between "Effectiveness" and "Recommendation Likelihood" and between "Familiarity" and "Recommendation Likelihood" are low. This indicates that there is no direct correlation between the NNs knowledge and greater efficiency or greater marketing of their worth and value (X. Pan, Huang, Nie, Wang, & Wang, 2024).

Charts Interpretation

- Histogram of Familiarity with NNs: If we closely observe the histogram given, they have a right-skewed distribution and most of the people rate their familiarity around the middle level which is of a moderate mark around 3 on the scale given below. This means that while some professionals are very conversant with NNs, a good number of them are minimally exposed or have a moderate understanding of this technology (Singh, Singh, & Devi, 2024).
- Correlation Heatmap: The correlation heatmap used below implies the findings even more by revealing that the relationships between the key Likert-scale variables are indeed rather weak even though the majority are positive. All of the above coefficients show fairly low coefficients and once again, this goes well with what was observed in the Pearson correlation test where, the three variables: familiarity, effectiveness, and likelihood of recommendation are not strongly correlated in this set (Ballav, Biswas, Dey, Sahu, & Basu, 2024).
- Boxplot of Effectiveness of NNs: The narrow range of the response variable related to "Effectiveness of NNs" is depicted as a boxplot below CO_VS1 The first graph indicates that there are variations in the responses, with some on the extreme ends of the scale. As much as 56 percent of responses are between 2 and 4, which reflects the general theory of moderately positive attitudes but the great dispersion of the results points to possible

dissimilarities of patient experience in the system between various cares, regions, or specializations (Masud et al., 2024).

- Bar Plot of Neurological Disorders Detected: Specifically, the bars in the plot depict that more NNs are applied for identifying conditions such as Alzheimer's Disease and Stroke than for other conditions such as Parkinson's Disease as well as Multiple Sclerosis. That is probably a reason why NNs are more widely used in some types of neurological diagnosis, which could be associated with the presence of data in these areas or the development of more efficient algorithms (Khosravi, Mohammadi, Zahiri, Khodarahmi, & Zahiri, 2024).
- Pie Chart of AI Tool Usage Frequency: From the same pie chart, it can be observed that AI tools are not yet on the 'Daily' usage in most of the respondents; rather, 'Weekly' or Even less was chosen by most of them. They observed that as AI is being integrated into medical imaging, it has not fully permeated the daily professional practice of several workers (Jahangir, Saeed, Shiwlani, Shiwlani, & Umar, 2024).
- Violin Plot of Recommendation Likelihood by Occupation: The violin plot represents a fairly large spread in the probability of recommending NNs depending on the occupation. The average suggested values were higher in AI researchers than in radiologists and neurologists, but the latter provided figures distributed over a larger range. It implies that those stakeholders who are more actively engaged in the creation of AI tools and applications will have a more positive attitude towards the technology, whereas the clinicians who are supposed the implement AI into routine clinical practice may still harbor some concerns or reservations regarding the technology (Aljohani et al., 2024).

Overall Interpretation

Since the combined results of the tests and charts suggest relative certainty and clear activation of medical imaging NNs, the absolute and relative equalization, the recognition and increased use of NNs in medical imaging reveal the relative variation in the perception of their effectiveness and recommendations. The lack of strong positive predictive values and inter-observer reliability presupposes that there is still no clear consensus regarding the role of NNs, and certain opinions might depend on one's occupation, experience, or specific applications of the latter. Even in areas of neurological diagnosis, for example, Alzheimer's disease and stroke, the use of AI has no longer increased, however, it is still not a routine technology in healthcare and not unanimously appreciated. The findings of this study underscore the need for increased work that focuses on the concerns and ways to enhance the application of NNs in medical imaging (SinhaRoy & Sen, 2024).

11. DISCUSSIONS

Hence, the result of the study provides useful insights into the current development of the NN in medical imaging, especially in the detection and diagnosis of neurological disorders. The responses to the questions detailed in Table 2 present a distribution that argues that NNs have not become integrated into healthcare fully but they are starting to make an appearance. This is particularly the case in clinical practice, which many respondents reported as being only moderately familiar with and using only rarely, let alone continuously and routinely as could be gleaned from scores of one percent and below out of one hundred. Perhaps, one of the most significant observations that can be made after analyzing the given results refers to the rather significant discrepancy between the neural network's potential and the actual application of that concept (Taha & Morren, 2024).

That is why, although it is seen that NNs show high efficiency in diagnosing various diseases including Alzheimer's disease and stroke, there is a clear segregation when it comes to using AI for different diseases. The bar chart indicating a shift to the right where these disorders are concerned indicates that the development and fine-tuning of the applicability of AI tools might be more pronounced here because of the availability of rich imaging data and large training sets. However, other conditions like Parkinson's, Multiple Sclerosis, and some more, seem generally slow in terms of the likelihood of receiving aid from AI in diagnosis, so, more work ought to be done on such diseases (Prabhod & Gadhiraju, 2024).

The low coefficients for the combined sets of possibilities involving familiarity, effectiveness, and the probability of recommendations indicate that, although some of the professionals may be aware of the existence of NNs, the same professionals may not necessarily hold them to be effective or efficient to recommend to others. This could be due to logistical issues as revealed through the survey results on challenges such as high costs, lack of interpretability, and small data sets. Low Cronbach's Alpha Coefficient was also established from the reliability test indicating that the measured variables are highly inconsistent and this supports the earlier impressions that perceptions about NNs are likely to differ across individuals depending on their experience or conditions (Xu & Mohammadi, 2024).

It also should provide a qualitative explanation for why several radiologists and neurologists exhibited relatively conservative recommendation probability compared to practitioners in other specialties, as illustrated in the violin plot below. Those practicing in clinical settings that involve direct patient care may appreciate some of these cautions for the following reasons: NNs are black boxes; there are legal/regulatory barriers; and questions of accuracy and clinical responsibility within the decision-making process. The authors indeed revealed that AI researchers exhibit a positive orientation toward the technology in question, which might explain the differences in engagement with the field: the participants provided more extensive information about AI concepts and their experience with the technology than the students did (Djenouri, Belhadi, Yazidi, Srivastava, & Lin, 2024).

Conclusion

This work is useful in revealing the current state of NNs in imaging techniques for diagnosing and managing neurological disorders. Even if AI is known to enhance diagnostic precision for various neural diseases such as Alzheimer's or stroke through the use of NNs, their implementation is still constrained. The results indicate variation in the level of awareness, utilization, and perceived efficiency among the various HCSPs regarding NN algorithms, which presents an implementation gap between their capabilities and easy implementation in real-world clinical settings.

Hypothesis 1 is in line with the study's findings as it was hypothesized that there is positive sentiment towards the future of AI, However, the study also shows that major hurdles including the high cost of implementation of AI, interpretability issues, and the use of NNs as a black box remain major barriers to its broad deployment. Also, it is necessary to note that low coefficients of associations connecting familiarity, effectiveness, and probable recommendations mean that there is still a considerable amount of work in education and increasing confidence of practitioners who might still not entirely trust such technologies.

Thus, while NNs are currently significantly changing some aspects of medical imaging, newer developments are required to define how AI will be implemented and to broaden its applicability in the diagnosis of various neurological pathologies. When using an AI technique, it will be important to translate the findings from the presented studies into receptor operational mode, making sure that artificial intelligence tools reach the target demographic, are stable, and are trusted by the staff.

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