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The Incorporation of Artificial Intelligence in the Identification of Neurological Disorders

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Abstract

With the rise of neurological disorders among a wide age bracket today, efficient and accurate diagnosis has faced some challenges. Due to the amount of time needed to observe the physiological symptoms of the brain as well as the behavior of the patient, certain neurological disorders can be mistaken for another. This led to the initial research question: To what extent can AI limit the amount of misdiagnoses by improving efficiency and reducing diagnosis time for neurologists in the United States? This study focused on monitoring three different artificial intelligence models and their efficiency to provide an initial diagnosis of a disorder based on an MRI scan. The three models that were compared were the Convolutional Neural Network (CNN), Multilayer Perceptron (MLP), and Recurrent Neural Network (RNN). Due to the similarity between the functioning of the CNN model and the typical human brain, it was hypothesized that the CNN model would be the most efficient. After running the brain scan through each model multiple times and averaging the data, it was found that the Convolutional Neural Network had the quickest response time and the most accuracy compared to the other models. This response time was based on the trained AI model's ability to make a diagnosis. A multiclass output was utilized for the final diagnosis results. Further implementation of AI models in the diagnosis process, especially CNN models, can lead to significant improvement in the field of neuroscience.

Introduction

People across a wide age bracket today suffer from various neurological disorders. The common challenge for science in this field is the amount of time it takes doctors to come to a final diagnosis and the risk of misdiagnosis. Often, because of the high demand for neurologists and the small number of doctors, these professionals have many patients, but not enough time to properly review brain scans. "Approximately 1 out of every 4 Alzheimer's patients are misdiagnosed, with an even split between false positives and false negatives” (Brauser, 2017). The conditions are often similar in terms of symptoms - for instance, dementia and Alzheimer’s disease or NESD (Non-Epileptic Seizures Disorder) and Epilepsy (Ferrie, 2006). Furthermore, the only form of diagnosis for syndromes such as autism and ADHD can be achieved through the observation of physiological signs. This can lead to incorrect prescriptions which can slow down or even worsen the healing process. AI (Artificial Intelligence) has already been thoroughly researched in the field of medicine, however it has not been used in this specific aspect. Artificial intelligence is defined as “the science and engineering of making intelligent machines, especially intelligent computer programs. It is related to the similar task of using computers to understand human intelligence, but AI does not have to confine itself to methods that are biologically observable” (IBM, 2023). The possibility of using AI to assist medical professionals combined with this research gap presented the problem statement: To what extent can AI limit the amount of misdiagnoses by improving efficiency and reducing diagnosis time for neurologists in the United States?

Despite the ongoing research of the implications of AI in the field of medicine, there is still a significant gap in research. Diagnoses based on the conclusions of artificial intelligence have not been used extensively due to concerns that may arise from technological malfunctions or the inability to use different aspects of a patient to put together a final case study/diagnosis. However, it is also important to acknowledge the human error that occurs with the diagnosis of neurological disorders. While relying entirely on AI to make diagnosis can lead to potential risks and might not have the human-to-human interaction that is currently present in the field of medicine, this technology can still prove to have significant advantages in gathering and analyzing more simple data (ie. vitals) and comparing brain scans more quickly. Doctors will still have to check over these conclusions, however, the incorporation of AI will minimize the misdiagnosis and provide a new perspective on each patient.

This study looks into the crossover between the two fields using brain models from EEGs (electroencephalogram) - “a test that detects abnormalities in your brain waves, or in the electrical activity of your brain” (Johns Hopkins, 2019) and MRIs (magnetic resonance imaging) - “a type of diagnostic test that can create detailed images of nearly every structure and organ inside the body” (Johns Hopkins, 2019). This was then applied to AI models to conclude which model is able to most efficiently diagnose a scan with precision. This can prove to be beneficial to researchers in both the field of neuroscience and AI as well as for patients since it can make the diagnosis process less expensive. Reducing the cost of these visits makes them more affordable for patients and allows them to receive the medical care they need. Furthermore, an advancement in this field will make it easier for doctors to focus on other, more intricate, aspects of the patient rather than initial vitals/diagnoses. These diagnosis processes allow for a more efficient way for doctors to not only diagnose patients, but also allows for reduced costs for both the hospital facility and the patient themselves.

In theory, the results from this study will ideally produce a more efficient form of diagnosis that relies on AI models. The comparison of the difference in brain folds will lead to fewer misdiagnoses and better recovery for individuals that do have certain neurological disorders. The information gained from this study can be used in addition to current developments and diagnosis methods in the field of neuroscience. This could have potential implications for other medical specializations as well.

Literature Review

To properly understand the research gap that is present in both the field of neuroscience and AI, it is necessary to analyze past studies that have been conducted. The research study started with a literature review of current sources in the field of neuroscience with the combinations of AI. After examining papers published over brain scans of the cross-section between the two fields, images published in prior studies were gathered to further run experimental tests.

Different AI models are currently being employed by the medical field and these will be used in this experiment to run the brain scans. Statistical data will then be gathered and presented regarding which AI model works the quickest. Some of these peer-published research papers also provided the outline of the manner in which their data was collected. This was then reflected in this experimental study. For many of these studies, there was significant research regarding MRI scans in oncology (for tumors, etc.), however, the brain scans weren't used as thoroughly to observe the difference in brian folds. This method can be effective in diagnosing neurological disorders (autism, Alzheimer's, etc.), but also to diagnose disorders such as Epilepsy/SUDEP which have been based more heavily on external tests, rather than looking at the internal, physiological symptoms (Walzl, 2019).

In a study done by Aksham and colleagues, a group of researchers at NYU, the structural differences in the brains of individuals with autism are compared to those without autism. The study emphasizes that certain trends have emerged in subsets of neurodivergent individuals, which may provide insights into the condition's underlying biology (Aksham, 2020). The study discusses the alterations in white matter, which plays a role in connectivity theory. Connectivity theory is also related to the brain structure in those with autism. The peer-reviewed paper also provides valuable information about the structural differences in the brains of individuals with autism, shedding light on how these differences may contribute to the condition. It highlights the heterogeneity of autism, emphasizing that there is standard brain structure for autistic individuals. However, while this study looked at the structural differences between neurotypical and neurodivergent individuals, there was no further research done on how AI can be implemented to observe these differences in the brain structures. In fact, there was very little in the field of neuroscience that observed using AI to analyze brain scans. The study focused on using human intervention to observe the structural differences. This study will aim to target this gap in research and implement the comparison of three different AI models to conclude the most efficient one.

Similarly in another study, Fan and colleagues, professors of neuroscience at Tsinghua University, discussed the historical developments in the field of artificial intelligence as well as the potential future implications it could have. It discusses the connection between both AI and brain science and how brain science has provided researchers with a foundation to further develop AI models. The article highlights that the developments in the field of neuroscience, specifically an understanding of the neural network, have benefitted AI and allowed it to develop significantly (Fan, 2020). Fan mentions another study where the multilayered nature of the brain allowed for the development of deep neural networks. According to Fan, the field of neuroscience can provide a large foundation as well as inspiration needed to develop current AI technologies.

A different study conducted by Mounsour and colleagues, university researchers in South Florida, delved into the current and future applications of AI in the field of neuroscience, specifically neuroradiology, with a focus on neuroimaging. The study discusses how the field of AI has had significant developments over the past few years with the ability to reach and potentially surpass human abilities. Certain AI models, such as deep learning algorithms, have been used to recreate neural networks, and have also been used to enhance the abilities of the AI (Monsour, 2022). This is especially prevalent in the field of neuroimaging. The source also discusses how AI is not only beneficial for imaging, but can also be used for scheduling purposes, reduced brain scans (specifically the number of MRIs), as well as decreasing the time it takes to diagnose certain neurological disorders. The use of AI can also be used to reduce the rate of misdiagnosis and increase the overall efficiency of brain scanning. However, the study is limited as there are no finalized conclusions or data points supporting the incorporation of AI for brain imaging.

By looking into current brain models and understanding the foundational structure, advancements in both fields can be made. However, there have not been significant advancements in using neuroscience to develop AI, which makes these studies limited in presenting a finalized solution. There is no clear data presented regarding the effectiveness of incorporating AI into analyzing brain scans nor is there statistical data regarding which model works the quickest for this specific purpose. While the sources state the benefits of AI as a tool, the physical differences among the brain structures of neurotypical and neurodivergent individuals, and the use of AI to recreate neural networks, there is no collaboration between these ideas. The development of a solution has not been carried out, and is only presented as a hypothesis. In addition, these studies do not factor the efficiency/speed of AI models into their research.

The conclusions of this study will also allow for the development of current AI models to make them more accurate in order to analyze human actions and behaviors as well as assess physical well-being. This incorporation of AI in diagnosis can drastically improve the field of medicine. The conclusions of this study will lead to a more efficient diagnosis of neurological disorders. Brain scans of both neurotypical and neurodivergent individuals can be used to develop artificial intelligence models. In this way, AI can be better used to diagnose existing diseases with basic physiological tests, making it easier for neurologists and other specialists to diagnose and see more patients.

Methods

The data collected will be analyzed through a variety of methods, however the main two research processes that will be utilized are an exploratory study and a case study. An exploratory study will allow for the complete analysis of both the fields of neuroscience and AI and incorporate the conclusions of other studies into this research. Meanwhile, a case study will allow for the in depth analysis of different instances of misdiagnoses in different patients, and will provide data regarding the negative impacts that the misdiagnosis had. After understanding the fundamentals of AI mechanisms and neurological disorders, through the data collection and analysis of other studies, further study was done on the mechanics of the brain, the specific areas (ex. prefrontal cortex), and the connectomics that allow humans to form pathways to process information. Connectomics is the field of neuroscience based on “understanding how individual neurons are connected to one another to form functional networks” (Caruso, 2023). The data collected from past studies with a focus on Connectomics was then used by mapping the different sections of the brain (implementing connectomics), allowing for the clear identification of how brains in neurotypical (NT) and neurodivergent (ND) individuals differ. This can be due to the brain folds, different neural network pathways, or other factors that will be presented in the findings sections.

The data used in the study is collected from both EEGs and MRIs. This data was then implemented by comparing existing AI models to see how well they can differentiate from the NT and ND brains. Afterwards, the specific areas where the AI model is lacking in identification was analyzed, and the most efficient model was then able to be concluded. This information can then also be implemented in a new AI system, which will be a hypothetical solution. This model could potentially be a combination of pre-existing AI models used in the medical field as well as a deep learning AI tool. The main purpose, however, is to find a current AI model that proves to be the most efficient for diagnosis.

The sampling method is the collection of the different brain scans in order to put them through different AI models. This method of data collection is justifiable because the ethical aspects are not being compromised as all scans were collected from previous studies that have already been published in peer-reviewed journals. The data collected from the brain scans will allow for the assessment of how much current AI models can be developed. This development will answer the question of how efficient the different AI model speeds can be to current neurologists and researchers in both the fields of medicine and AI.

The AI models that were used in study are listed below (Klingler, 2021):

Artificial Intelligence (AI) - It is a subfield within computer science associated with constructing machines that can simulate human intelligence. AI research deals with the question of how to create computers that are capable of intelligent behavior. The subsections are Machine Learning and Deep Learning.

Machine Learning (ML) - is a subset of AI associated with providing machines the ability to learn from experience without the need to be programmed explicitly; example programs include YOLOv3 and Edge Computing.

Deep Learning (DL) - A deep learning model, or a DL model, is a neural network that has been trained to learn how to perform a task, such as recognizing objects in digital images and videos, or understanding human speech, example programs are ResNet and SAM.

The duration, impact, and speed of the AI model was then measured and the specific data points were found. In order to ensure a fair trial between the three models selected for this experiment, the MLs were all trained with a previous dataset of labeled MRI scans. This labeling highlighted the distinction between different neurological disorders commonly seen in brain scans (ie. Alzheimer’s, Parkinson’s, Epilepsy, etc.). After the data passes through the initial scan, the prediction is compared to the original scan and the model then optimizes itself to more accurately diagnose the disorder. This trial is run an equal number of times for all three models. The trials continued until at least one model reached a negligible amount of inaccuracy. Then, the actual speed of the models during the inference phase (forming a diagnosis) was tested. This data included the speed the AI models completed the task measured in flops. Finally, a table with the comparisons was created. The different types of neurological disorders that can be diagnosed were also included, which was the qualitative aspect of this research.

The main tools utilized, as mentioned above, were the different AI models that were used for testing as well as the computer programs used to show the data comparison. The programs used were Excel or Google Sheets to create tables and models. The study was initially going to utilize the R software, but inputting minimal trials into such a large program was not an efficient use of the already contracted time limit. These tools were necessary in order to accurately represent the data found and to make a credible conclusion that reflects the benefits of AI in the medical field.

The research design included initial gathering of MRI scans, and then pre-existing AI models were used to create an initial diagnosis of a neurological disorder. The AI models were then analyzed to see where the diagnosis of these disorders was lacking. By looking at the crossover between using brain models (based off of MRI and other brain imaging technology) and applying it to AI models to further develop them, a solution to misdiagnosis for neurological disorders will be created, which is the main purpose of this study.

In addition, incorporating AI will make diagnoses and hospital visits less expensive. Reducing the cost of these visits makes them more affordable for patients and allows them to receive the medical care they need. This can also make it easier for doctors to focus on other, more intricate aspects of the patient's illness rather than initial vitals/diagnoses. Another benefit of this research project is developing current AI models to make them more accurate to analyzing human actions and behaviors as well as assessing physical well-being. This can drastically improve the field of medicine. The speed of the data of AI models was more interpreted than analyzed as this study did not have access to a doctor's opinions of specific AI models.

The concluding data when presented in a table will be interpreted in a hypothetical sense. This way, future researchers might be able to more accurately replicate the study and come up with their own conclusions. Using both an experimental study and a case study allowed this study to delve deeper into the cross-sections between neuroscience and AI. This can also provide a wider perspective on the details associated with the challenges of diagnosing neurological disorders. The potential implications, based on the conclusions of this study, can also be tested and applied directly to the field of medicine. These research methods allowed this study to focus on the real-world applications and provided insight into the current status of the artificial intelligence field and neuroscience.

Data Collection

The data collection for this study started with the collection of brain scans that have been published in past research papers, so there were few ethical and legal concerns present. To reiterate, the initial research question for this study was "Can AI limit the amount of misdiagnoses by improving efficiency and reducing diagnosis time for neurologists in the United States?”

The process of measuring the individual speeds of each AI model was done at a local biology-computer science lab. The table for data comparison was made by running the same image through all of the models as a control. Each model was run for the same amount of time to maintain consistency and each model was tested for four trials in order to find the most precise/accurate results. After gathering four data points for each of the AI models, these numbers were averaged to create one final data point as a comparison.

The main variable that was tested when running the images through the AI models was the speed during the inference phase (how quickly it identified the neurological disorder present in the brain scan after training), which was measured through a process called “benchmarking.” According to Shana Lynch at Stanford University Institute for Human-Centered AI “a benchmark is essentially a goal for the AI system to hit. It’s a way of defining what you want your tool to do, and then working toward that goal” (Lynch, 2023). Benchmarking is a tool used to compare different technologies, especially AI models, in order to test which one is most efficient. Accuracy was also available to test, however, there were multiple parameters such as the scale of accuracy and practicality of real-world implications, which made it a difficult variable.

The speed of these AI models were measured in flops, which stands for floating point operations per second (Lopez, 2023). Machine learning in the field of healthcare and engineering uses this unit of measurement in order to test the speed that an AI model can identify an image. The input of the ML models was the MRI image of a brain diagnosed with Parkinson’s, however the methods differed slightly among the models. The CNN model received a 3D image array to allow it to process spatial patterns. The MLP model received a 1D feature vector of the same image. The RNN model received sequential scans over a period of time. The output can be defined as multiclass. The models were all provided with predefined categories of neurological disorders. These disorders are the following: Alzheimer’s Disease, Parkinson’s Disease, Epilepsy, Amyotrophic Lateral Sclerosis, Dementia, and Intracranial Aneurysm. The model either determined a specific disorder or stated “no disorder” if nothing was detected. If a disorder was detected, the model was prompted to assign a percentage probability score of the likeliness of the disorder to determine the final diagnosis.

In order to create a comparative study of the existing AI models in the field of neuroscience, it was necessary to narrow down to three models. As of 2023, according to CEO of ContentScale Justin McGill, there are currently around 14,700 AI models that exist (McGill, 2023). Even creating a range of AI models based in the field of healthcare still leaves thousands of models to test. For this reason, this study decided to narrow down to only Deep Learning models (DL), specifically Artificial Neural

Network modes or ANN. Under the subsection of ANN models, the specific models that were tested for efficiency were the Multilayer Perceptron (MLP), Recurrent Neural Network (RNN), and Convolutional Neural Network (CNN). These models were used for comparison and data collection in this study due to their current prevalence in the medical field and within the crossover between AI and neuroscience. The hypothesis, formulated based on the underlying structure of these AI models, is that CNN will prove to provide the most efficient results. This is because the structure of the model closely replicates the human brain.

ANN (Artificial Neural Network)

The main type of AI model that was used in this study was an ANN (Artificial Neural Network) Model. According to IBM, “a neural network is a machine learning program that makes decisions in a manner similar to the human brain, by using processes that mimic the way biological neurons work together to identify phenomena” (IBM, 2022). Neural networks in the field of neuroscience and AI research incorporate the use of artificial neurons that mimic human brain activity. Due to the fact these models were the closest to the human brain structure, it was chosen as the main tool in this study in order to conclude the most accurate speeds of the AI models. ANN models are a subsection of the overarching field of artificial intelligence and they fall into the category of Deep Learning Models, which as defined previously, is a neural network that has been trained to learn how to perform a task, such as recognizing objects in digital images and videos or understanding human speech. The types of ANN models were split into further subsections in order to clearly identify the AI model with the greatest efficiency.

Multilayer Perceptron

MLPs are well-known in the field of neuroscience due to their ability to solve nonlinear problems - a task many other AI models have not yet been developed to perform. The underlying principles of the way MLPs function are based on multilayered interconnected nodes, each layer serving a different purpose. The first, bottom layer is the input layer also known as the visible layer. This layer makes a single connection between each neuron and input value. The second is the hidden layer, which is not directly connected to the visible layers. In addition, each singular neuron in the hidden layer creates one direct output. The main benefits of using MLP AI models to analyze brain scans is the ability to create complex connections between the neurons and the input and output values. This makes them not only useful for brain scan imaging, but for a variety of other applications in the field of healthcare. The MLP model used for this study was trained on the dataset MNIST to establish a baseline performance. The MRI scan was then applied to the MLP in the final experiment along with the other AI models.

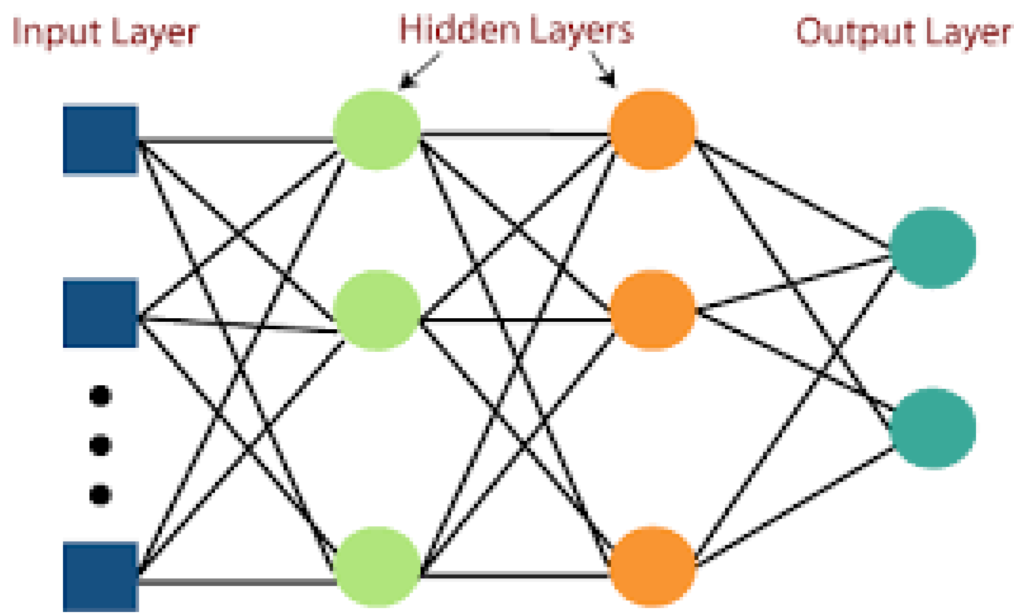

FIGURE 1: The image above shows the multiple layers of the MLP model and data is typically run through it (Javatpoint, n.d.)

Recurrent Neural Network

Recurrent Neural Networks (RNNs) are a class of artificial neural network models designed to effectively process sequential data by incorporating feedback loops within their architecture. Unlike traditional feedforward neural networks, RNNs possess connections that form directed cycles, enabling them to retain and utilize information from previous time steps. This feature allows RNNs to use contextualization information using sequential data and also allows the model to adapt based on new information added. It can also perform tasks such as language processing, time series prediction, and speech recognition. The specific RNN model used for this study was SimpleRNN due to its compact and minimalistic software structure, which makes it easier to input data.

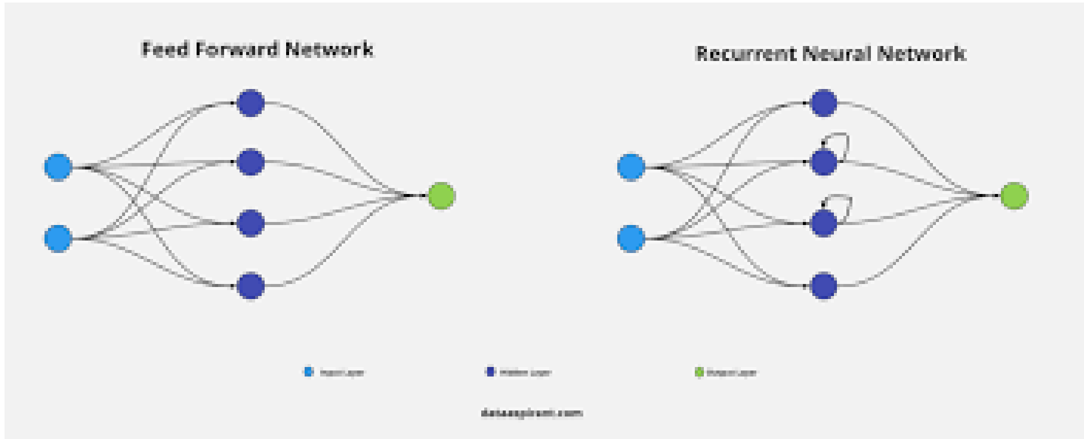

FIGURE 2: The image above compares a feed forward network with the basic structure of the RNN model and how data is processed through it (Das, 2020)

Convolutional Neural Network

Convolutional Neural Networks (CNNs) are significant in the field of deep learning, and are well-known due to their abilities to process and extract data in class-based or hierarchical systems such as images and time-series signals. The creation of the model is closely based on the mammalian brain. CNNs utilize special layers known as convolutional layers to efficiently detect patterns and spatial dependencies within input data. The initial layers consist of different filters that can adapt as new data is inputted and can connect the artificial neurons to create new networks. The deeper layers reduce the spatial dimensions of the image, allowing for the transformation of an object from 3D to 2D, which allows for the model to easily identify images. The adaptiveness of the model enables the network to learn increasingly abstract and complex representations of the input data. It also makes use of a non-linear activation, different from the MLP AI model. RNN models do oftentimes use a non-linear activation function, however the primary difference from the CNN model lies in the architecture (sequential versus spatial data processing). Non-linear activation proves to be more effective in CNNs due to its hierarchical representation and use of ReLU (Rectified Linear Unit). The use of ReLU trains the CNN model to formulate faster analysis by separating the important information from the less crucial information in an image. This element also allows the model to identify lower-level features (ie. edges), but also deeper, more complex patterns, which allows the CNN models to identify unseen data within an image. This multi-level abstraction can't be seen within the non-linear activation of RNNs. The specific CNN model used for this study was Conv2D as it has the maximum number of layers which enabled it to deconstruct even more complex images.

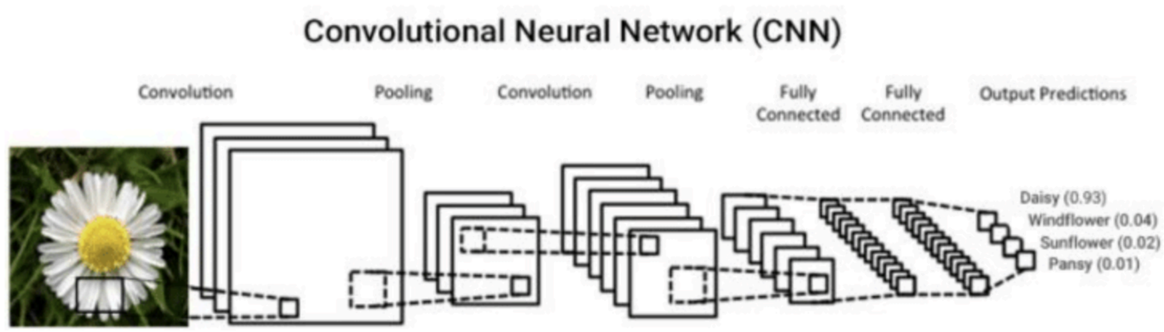

FIGURE 3: The figure above shows how an image is processed using the CNN AI model and how the final result is identified (Adusumilli, 2019)

After the initial training of the models was executed, it was found that the CNN model required the fewest number of training trials to accurately assess a disorder, completing the process in only 4 trials. The training process was then stopped in order to ensure accuracy. In order to record the data into a single graph, an Excel spreadsheet and Google Sheets were used. The specific ANN models described above were already in use by a local lab, so this experiment didn't require any prior calibration or testing of the softwares. As can be seen in the figure below, the speeds of these models were tested in the four trials shown. The brain scan below was inputted into each model and the number of petaflops it takes to identify the neurological disorder was measured (Rouse, 2023).

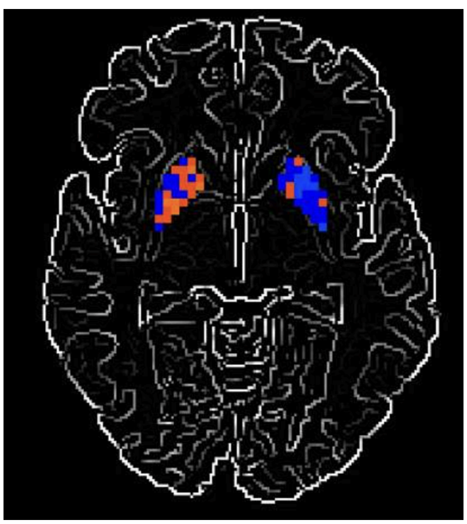

FIGURE 4: Brain scan of an individual with Parkinson's Disease collected by researchers at the *NIH* (*NIH,* 2016)

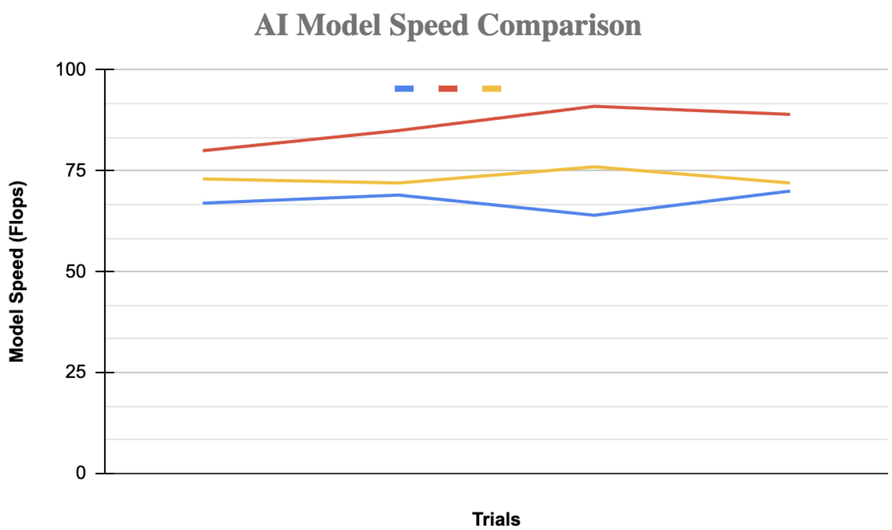

FIGURE 5: The graph above compares the three AI models tested (MLP, CNN, and RNN in order of the colors) and their respective speeds in flops.

67	69	64	70
80	85	91	89
73	72	76	72
Trial 1	Trial 2	Trial 3	Trial 4

TABLE 1: The table above shows the specific speeds recorded in flops for each trial in the order MLP, CNN, and RNN respectively.

In *Figure 5* above, the red line represents CNN, the yellow line represents RNN, and the blue line represents MLP. *Table 1* shows the individual speed per flop for each AI model. After the four trials for each model were completed, the individual speeds in each row were averaged to compare a single data point. The averaged speed of the first row was 67.5, reflecting the speed of the MLP model. The second row had an average of 86.25 reflecting the speed of CNN. The third row had an average speed of 73.25, reflecting the speed of the RNN model. As can be seen from these numbers, the CNN model had the quickest speed in identifying the neurological disorder, Parkinson's, compared to the other two with more than a 10 point difference to the RNN model and almost a 20 point difference to the MLP model. Based on prior research on the construction of each AI model, this proved the initial hypothesis correct because the CNN model had the closest structure that replicates the manner in which the human brain functions. Results from this could provide a further integration in the bioengineering field and an increased production in neuro-CNN AI models. Although there are some gaps present with this study as there were not multiple brain scans tested, the data points found can still have implications in the field of neuroscience and can improve the process of diagnosing neurological disorders for doctors. In addition, this finding can provide benefits to bioengineering when creating new AI models in order to diagnose other medical issues.

Conclusion

This study looked into Deep Learning AI Models which are commonly used in the field of neuroscience, specifically Artificial Neural Network models (ANN). ANN was further broken down into three subsections - CNN, MLP, RNN - which were the three models that were tested for speed (in flops) and compared to each other in order to conclude the most accurate results. It was found that CNN was the most efficient AI model due to its ability to identify a brain scan the most accurately compared to the other AI models in the study. This difference in speed can be attributed to the structure of the CNN model, specifically the spatial hierarchy and parallelization. The convolutional layer format learns the local features of the image provided, which reduces the overall number of computations required compared to the MLP or RNN model. In addition, the CNN model contains processes such as pooling and convolution. This allows the various layers to analyze the image independently, perform the operation at different positions, and then divide this data into smaller tasks to be run parallely across the GPU. This same process can't be applied to MLPs due to their fully connected layers. It also doesn't work effectively in RNNs because it runs on sequential processing that analyzes the data individually, therefore taking more time.

The main benefit of this study is the clear numbers that show the comparison between the different models, which provide strong evidence for which model is best for analyzing a brain scan and providing a diagnosis. However, one of the limitations encountered in this study was the inability to test multiple neurological disorders and other variables present with the AI model (ie. accuracy).

There are various variables present when deciding how efficient an AI model is, however due to lack of resources and expertise, these elements were not able to be tested. This study, however, can be easily replicated in other areas in the field of medicine, as long as researchers have access to AI model databases and an image that can be used, allowing the results to have useful implications. Diagnostic times in the future can be reduced drastically and patients can be provided with results within the same day, sometimes within hours. Further implementation of the CNN AI model into the field of neuroscience can also reduce the costs of the testing for hospitals.

Future research in the field can further look into the role that Connectonomics plays in the diagnosis of neurological disorders and how the brain folds in individuals with different neurological disorders or impairments (ie. alcohol overdose) compares. This further research can lead to treatments for both immediate and chronic diseases in neuroscience and can leave a lasting impact in the world of healthcare.

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