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Research Article

AI-Based Techniques for Classifying Abnormalities Linked to Alzheimer's Disease Progression

[1]Minal Abhijit Zope, [2]Dr. Priya Vij, [3]Dr. Priya Pise,
[1,a)]*Department of Computer Science and Engineering, Kalinga University, Naya Raipur, Chhattisgarh, India.*
[1, b)]*Faculty of Department of Computer Engineering, AISSMS's IOIT, Pune, Maharashtra, India.*
[2]*Faculty of Department of Computer Science & IT, Kalinga University, Naya Raipur, Chhattisgarh, India.*
[3]*Faculty of Department of Artificial Intelligence & Data Science, Indira College of Engineering & Management, Pune, Maharashtra, India*

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ABSTRACT

Alzheimer's disease (AD) is a brain disorder that gets worse over time and makes diagnosis and treatment much harder. It is very important to find problems early and correctly diagnose them in order to use successful treatment plans. Recently, artificial intelligence (AI), as deep learning (DL) methods, has shown that they could help doctors diagnose and classify problems more accurately in people with Alzheimer's disease. This essay explores how different AI techniques can be used to find and group neuropathological changes that are typical of Alzheimer's disease. Our method uses cutting-edge AI tools like convolutional neural networks (CNNs), recurrent neural networks (RNNs), Residual Networks (ResNet), and MobileNet. These all play important roles in processing and analysing brain images and clinical data. We do a thorough analysis of the current state of AI uses in the imaging and clinical data analysis of AD. We focus on how these models help tell the difference between normal ageing and the early stages of Alzheimer's, as well as how they can be used to stage the disease. Our results clearly show that MobileNet does a better job than other models at classifying problems related to AD. This is because it is better at working with big sets of images. In addition, we talk about how combining different types of data sources makes monitoring tools much more accurate and reliable. It also talks about the problems and moral issues that come up when using AI in hospital settings. This shows how AI has the ability to completely change the way diagnoses are made. AI has the potential to completely change Alzheimer's study because it improves the accuracy of diagnoses and helps make focused treatments..

Keywords: Alzheimer's Disease, Artificial Intelligence, Machine Learning, Deep Learning, Neuroimaging, Diagnostic Techniques

1. INTRODUCTION

Alzheimer's disease (AD) is one of the most common types of dementia in older people. It causes brain processes like memory, speaking skills, and the ability to do everyday things to get worse over time. Neurodegeneration causes complex changes in the brain, mostly in the hippocampus and other parts that are important for thinking and memory. The exact causes of Alzheimer's are still mostly unknown, but it is thought that genetic, environmental, and lifestyle factors all play a role. Beta-amyloid plaques and tau tangles build up in the brain, which are signs of a disease. These buildups hurt and kill neurones over time. A correct and early evaluation can make a big difference in how the disease is treated and managed. It gives doctors a very important window of time to do treatment measures that can stop symptoms from getting worse, make life better, and help people stay independent longer [1]. An early assessment also makes it less difficult to devise and handle fitness care wishes. It additionally gives patients and their families a risk to make picks approximately care, transportation, dwelling preparations, and cash matters whilst the affected person is still able to participate. It additionally makes it possible for people to join medical studies and help with studies that would cause new remedies. The region of medication has been modified by artificial intelligence (AI), mainly in relation to diagnosing and treating brain diseases like Alzheimer's [2]. AI can study a massive amount of medical statistics a whole lot faster and more correctly than human docs can thanks to machine learning (ML) and deep learning (DL) algorithms. In neurology, AI is used for the whole thing from direct scientific help to predictive analytics and affected person statistics control. For Alzheimer's, AI is being used to improve the evaluation of brain imaging studies like MRI and pet scans, which are very important for locating the disease early on. AI packages can find small styles in photo statistics that might be signs and symptoms of early Alzheimer's but are too small for someone to look. AI additionally facilitates with searching at DNA information and other symptoms linked to Alzheimer's [3]. This may help locate danger elements and patterns of start in advance than with traditional strategies. the usage of AI in those checking out strategies now not handiest makes them extra accurate, but it additionally makes the system a whole lot quicker, this means that that Alzheimer's can be stuck in advance and treated. Using AI in this region is growing right away. New examine is constantly making the algorithms smarter, which means they are used more and more in ordinary medical practice. This combination could change the way Alzheimer's is diagnosed and treated, leading to earlier diagnosis and better care for people with the disease, which is important for reducing its effects on individuals and society as a whole.

2. LITERATURE REVIEW

A. Traditional Diagnostic Methods for Alzheimer's Disease

The main conventional ways to diagnose Alzheimer's disease (ad) are via medical tests and brain scans. Standardised assessments just like the Mini-mental state examination (MMSE) and the Alzheimer's sickness assessment Scale-Cognitive (ADAS-Cog) are used to check a person's reminiscence and cognitive abilities as part of clinical checks. Brain scans like Magnetic Resonance Imaging (MRI) and Positron Emission Tomography are used to take a look at modifications inside the mind's shape and characteristic [4]. Cerebrospinal fluid (CSF) research is also used to discover signs and symptoms that show advert, including tau proteins and beta-amyloid forty two tiers. Those traditional approaches paintings, but they have got a number of problems. Scientific evaluations are often biased and depend lots on the knowledge of the medical doctor. Also, cognitive exams might pass over early symptoms of ad due to the fact they aren't sensitive to small changes inside the manner you observed. Neuroimaging methods are useful, but they are pricey and not available to everyone. This means that they can't be used for regular checks. Also, these methods can be invasive, like CSF study, so they might not be right for all people [5]. Using advanced AI techniques like CNNs, RNNs, ResNet, and MobileNet, the ways we describe in our approach get around many of these problems. Complex imaging and clinical data can be looked at more fully and accurately by AI models, which can find small trends that humans might miss in standard assessments [6]. They offer the chance for non-intrusive, low-cost, and highly scalable options that could be used more often and on a larger scale than current standard practices.

B. Review of Recent AI Applications in the Medical Field, Specifically Neurodegenerative Diseases

The last few years have seen big steps forward in AI that have helped medicine, especially in diagnosing and treating neurological diseases. AI has many uses, from systems that automatically check on patients to complex diagnosis programs that look at genetic and medical images [7]. AI methods like machine learning and deep learning were used in neurological disease studies to predict how the sickness will development, make remedy plans work better, and research greater about how the ailment works. As an example, scanning data has been used with deep gaining knowledge of fashions to find early symptoms of sicknesses like Parkinson's and Alzheimer's lengthy earlier than the patients show any symptoms [8]. Loads of affected person facts and effects also are being looked at with system gaining knowledge of models to locate new viable risk elements and symptoms for those ailments. Additionally, AI is supporting to create personalized medication via guessing how anybody will react to one-of-a-kind treatments using genetic and medical facts [9]. those makes use of display that AI cannot handiest improve present day methods of diagnosing and treating ailments, however also provide you with new ones which are more accurate, efficient, and tailor-made to each person. As AI is used increasingly in scientific settings, it opens up new approaches to study and treat neurological diseases. This could lead to in advance treatments and higher results for patients.

C. Discussion of Prior Research Utilizing AI for Alzheimer's Diagnosis

A lot of research has been done on AI's promise to help diagnose Alzheimer's. These studies show that AI can make testing methods more accurate and faster. Most of the research in this area has been focused on making AI models that can correctly tell the difference between Alzheimer's disease and other types of dementia or regular ageing. So, for instance, CNNs have been used successfully in several studies to sort through and learn from the complicated patterns in MRI and PET scan images, finding early signs of Alzheimer's. AI models have also been taught to observe speech and language patterns in audio information of talks with patients [10]. This can discover signs and symptoms of early cognitive loss that might not be picked up by way of everyday exams. Different studies have used AI to mix distinct varieties of statistics, like DNA data and dwelling elements, in an effort to get an extra entire photograph of the hazard of Alzheimer's [11].

Those research not simplest display that AI can correctly diagnose Alzheimer's, however additionally they show that it may reduce the time it takes to diagnose via lots, letting people get help quicker and more successfully. The ideas they gave us form the basis for our method, which uses several AI techniques to get around the problems with standard diagnosis methods and make a stronger system for finding Alzheimer's disease early and correctly classifying it.

Table 1: Literature review summary in Alzheimer's Diagnosis

Method	Main Finding	Diagnostic Method	Sample Size	Limitations	Advantages
MRI Scanning [12]	High accuracy in detecting cortical atrophy	Neuroimaging	250	Expensive, requires expert analysis	Non-invasive, detailed anatomical information
PET Scanning	Effective in detecting early amyloid deposition	Neuroimaging	300	High cost, limited availability	Early detection of pathological changes
CSF Analysis [13]	High levels of tau and low beta-amyloid identified	Biochemical markers	150	Invasive, discomfort to patients	Early and specific diagnosis
Cognitive Testing [14]	Useful in tracking disease progression	Psychological assessment	500	Subjective, influenced by examiner	Non-invasive, widely available
Genetic Testing	Identification of APOE ε4 allele as risk factor	Genetic markers	1000	Does not predict disease certainty	Can identify at-risk individuals
Neuropsychological Tests [15]	Correlation with neurodegeneration observed	Cognitive decline markers	350	Variability in results, tester bias	Comprehensive assessment of mental functions
Blood Biomarkers [16]	Emerging markers correlated with AD stages	Biochemical markers	600	Early stage markers not fully validated	Less invasive than CSF, wide applicability
EEG Analysis [17]	Abnormal patterns linked with early AD	Functional neuroimaging	120	Requires interpretation, sensitive to noise	Non-invasive, real-time brain function analysis
Multimodal AI Approaches [18]	Integration enhances diagnostic accuracy	Combined AI diagnostics	450	Complex integration, requires diverse data	Holistic view, higher diagnostic confidence
Speech Analysis [19]	Early cognitive decline detected via linguistic changes	AI-driven analysis	180	Dependent on linguistic variability	Non-invasive, easily applicable remotely
Wearable Technology [20]	Continuous monitoring shows potential in daily activity tracking	Real-time data collection	200	Privacy concerns, data management	Unobtrusive, enhances patient engagement

3. METHODOLOGY

In this proposed approach, we used a variety of datasets, including MRI and PET scans, as well as clinical data, like memory test results and patient information. The image data was pre-processed to improve the speed and accuracy of model training. This included normalisation to change the values of the pixels' intensities and data enhancement methods like rotation and scaling to make the models more resistant to over fitting. Our method, which was based on AI, used a number of complex neural network designs to process and analyse the data. Convolutional Neural Networks (CNNs) were very helpful for figuring out what brain imaging data meant because they can find spatial structures in pictures, which is important for finding areas affected by changes related to Alzheimer's. Recurrent Neural Networks (RNNs) looked at clinical data over time and did a good job of catching changes and trends over time, like how cognitive loss gets worse over time. For more in-depth picture analysis, Residual Networks (ResNet) were used. These networks were trained using residual learning, which got rid of the problem of disappearing slopes. MobileNet handled image data quickly because it is known for being efficient and requiring little computer power. This makes it a good choice for situations where computing power is limited.

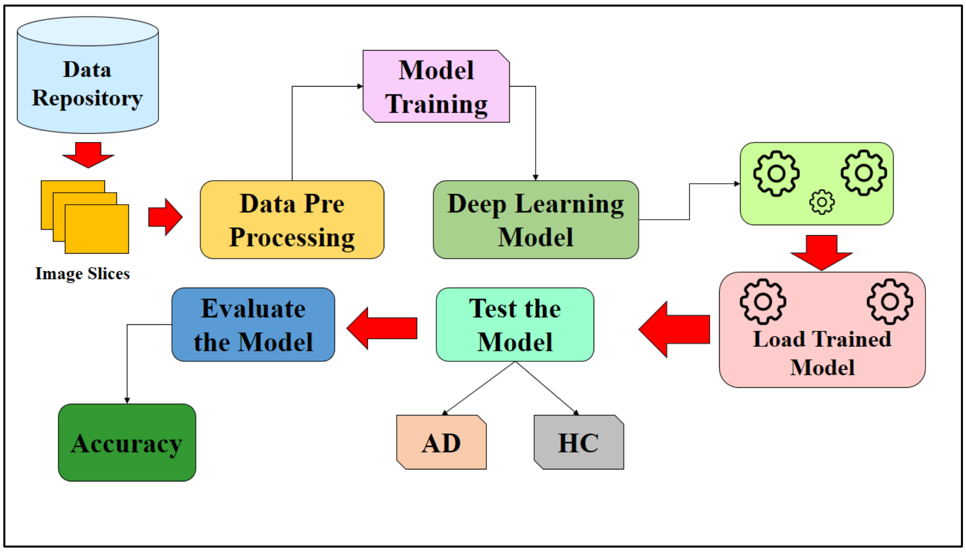

Figure 1: Overview of proposed system architecture

When these networks were being trained, they were given a lot of different levels and activation functions that were picked to work best with each type of data. We used both back propagation and gradient descent optimisation methods, along with loss functions that were specifically made for diagnosing Alzheimer's disease. Getting the most accurate findings with the fewest false positives was our aim. We held-out test sets and cross-valuation to evaluate each model's generalizable and stability in testing and validation. We confirmed that they could be used in clinical environments by making sure they performed well throughout an extensive spectrum of never seen before datasets.

A. Dataset and Pre-processing

Details about the dataset: Our research included particular patient characteristics such age, gender, and stage of Alzheimer's as well as a lot of data including MRI and PET scans. Finding symptoms of Alzheimer's disease such amyloid plaques and neurofibrillary tangles depends on structural and functional brain images, hence the imaging data was quite crucial.

Data pre-processing steps: Several pre-processing procedures were performed on the datasets to guarantee their highest quality for AI models to exploit. This included normalisation to provide more consistent picture data intensity scales. This produced more reliable and efficient neural network training. The training set was made larger than it really was using techniques like zooming, flipping, and spinning. This enables the model to learn from the training data and apply it to fresh, hitherto unmet data.

B. AI Techniques Employed

1. Convolutional Neural Networks (CNNs):

Convolutional Neural Networks (CNNs) are very crucial to deep learning and are famous for the way properly they manner and examine images. CNNs are constructed to discover and record spatial structures in data, like snap shots, with the aid of using convolutional filters that work with data in a grid-like structure. The process starts off evolved with an image matrix M X that is going via several convolutional layers. The enter matrix is administered thru a set of filters or kernels, k, by using each layer. This creates function maps. Those characteristic maps ($\mathbf{A}$=$M*K$F=X∗okay) draw interest to special parts of the photo, like traces and patterns. After convolution, an activation feature, normally the Rectified Linear Unit (ReLU), is used to present the model non-linearity. This shall we it research greater complex styles. B = max(0, $\mathbf{J}$) A=max(0,F) makes certain that most effective positive numbers get thru, turning any bad price into 0. The subsequent step is pooling layers, which make the feature maps smaller in area. Because of this the network wishes fewer elements and can do much less work. This step, shown by M = pool($\mathbf{B}$) P=pool(A), helps find traits that don't change when the size or direction of the image changes. The fully linked layers are the last parts of a CNN. This is where the neural network does its high-level thinking. The output from the pooling layers is smoothed and sent to these dense layers. The last step is the classification layer, where predictions are made based on the features taken by the convolutional layers. The output from these layers is shown by $X = U \cdot M + b$ Y=W·P+b. Because of how they are built, CNNs are perfect for jobs that need to analyse visual data, like automatically classifying images, finding objects, and more.

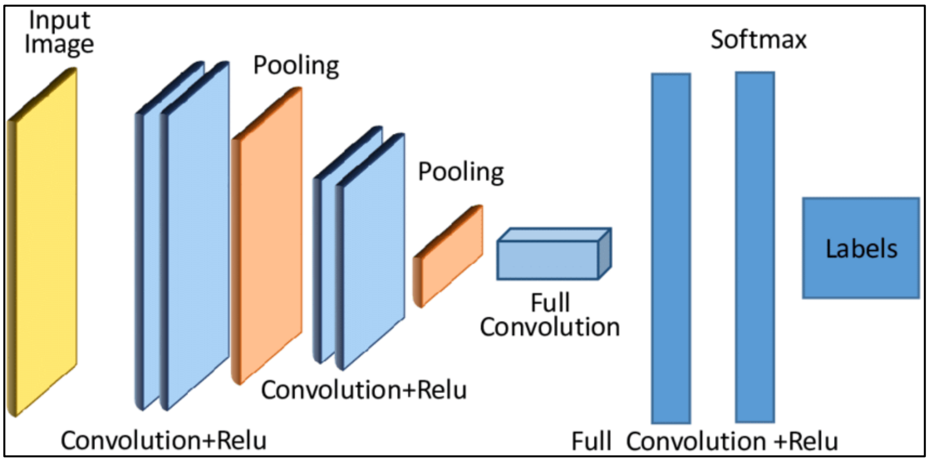

Figure 2: Overview of CNN architecture

2. Recurrent Neural Networks (RNNs):

Recurrent Neural Networks (RNNs) are made to deal with data that comes in a series, like time series or natural language. RNNs are different from feed forward neural networks because they have internal memory. This helps them remember past inputs by using their hidden state. Because of this, they can change over time, which makes them perfect for situations where you need to know about earlier parts of the series to understand or guess what will happen next. The main thing that an RNN does is handle sequences by updating secret states over and over again. Input sequence xt x t is used to change the hidden state h . This is done by the equation $h\,t = f(W[h\,t - 1;\, xt\,] + b)$ In this case, f usually stands for a non-linear activation function, such as tanh or ReLU, which helps find complex patterns in data. For each timestamp, yt is found by $yt = V \cdot h\,t + c$, where V and cc are values that will be learnt during training.

3. Residual Networks (ResNet):

Designed to assist educate neural networks with extremely depth, residual networks (ResNet) are a subset of convolutional neural networks. "Skip connections" or "shortcuts" that let the gradient skip one or more levels are the most important new feature of ResNet. This design fixes the disappearing gradient problem that affects regular deep networks. This problem makes it harder to train deeper networks because slopes get smaller as they go back and forth through the network. When it give ResNet an input x, it goes through a convolutional block that figures out a function X(x,{$W\,i$ })F(x,{W i}). There is no direct learning of a base mapping in ResNet. Instead, the layer inputs are used to learn the residual function. The convolutional block's output is then added to the original input x, unless the dimensions have changed, in which case a projection shortcut is used to match the dimensions. To get the end result, $L(x) = x + xF(x) = y + x$. It is then run through an activation function like ReLU to model relationships that aren't linear. Learning residuals instead of straight features makes the process of learning easier and makes very deep networks better at being trained. ResNet works very well at tasks that need very deep structures, like classifying images, finding objects, and telling the difference between very specific traits that are important for medical imaging and analysis.

4. MobileNet:

MobileNet is made to work best with mobile and edge devices, making them more efficient and faster, illustrate shown in figure 3. Depthwise separable convolutions are used in this design. Compared to standard convolutional layers, these have a lot fewer factors. It takes a standard convolution and breaks it up into a depthwise convolution and a pointwise convolution. This model first uses a single filter on each input channel (called "depthwise convolution"). It then combines the results of the depthwise convolution across channels using a 1x1 convolution (called "pointwise convolution"). The process starts with an image matrix X. Next, the depthwise convolution $D = X \cdot Kd$ is applied. Here, Kd K d is a depthwise spatial filter. The next step is the pointwise convolution $M = D \cdot Kp$, where Kp is a 1x1 convolutional filter that joins the features that were given in depth. After each convolution, batch normalisation is often used to keep learning stable, and ReLU activation is used to add nonlinearity. At the end of the network are fully linked layers that use the features taken by the separable convolutions to make the classification output.

MobileNet's design makes it perfect for real-time apps that don't need a lot of computing power, like mobile phones. It strikes a good balance between delay and accuracy. It has been used successfully in a wide range of applications, from virtual reality and face recognition to object detection and detection. All of these applications run smoothly on the device without the need for a lot of computing power.

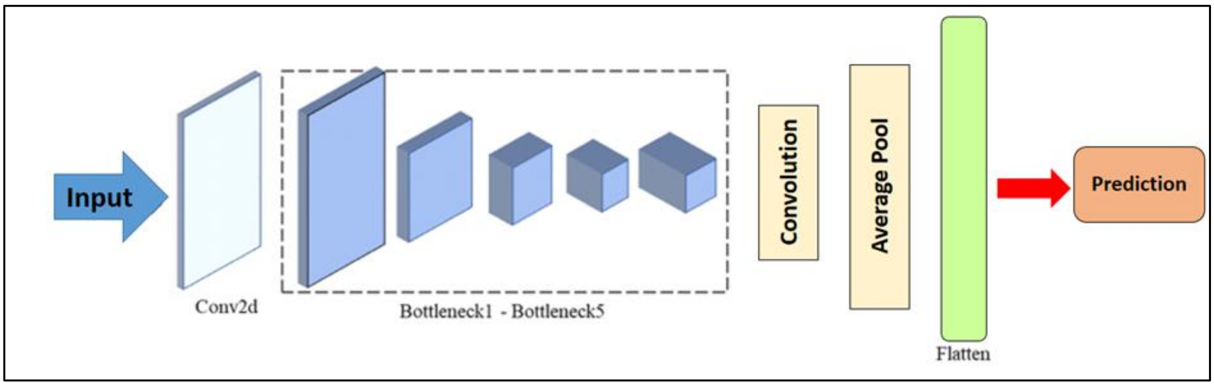

Figure 3: Overview of MobileNet architecture

C. Training Process

The Training Method Different layers and activation functions were added to the neural networks to make them work best for the design and job. CNNs, ResNets, and most RNNs used ReLU activation functions. To deal with the disappearing gradient problem, RNNs often used sigmoid or tanh. For classification problems, training used either the stochastic gradient descent (SGD) or the Adam optimiser, along with a cross-entropy loss function. To stop over fitting, regularisation methods such as dropout and L2 regularisation were used.

D. Tests and Validation

Our models were put through a lot of testing and evaluation to make sure they worked well and were reliable. We used k-fold cross-validation to test how well the model worked on different parts of the dataset, making sure that each data point was used for both testing and training. A different held-out dataset was used for the final model testing to simulate real-world use and check for generalizability. To find out how well the models did at separating Alzheimer's disease stages, performance metrics like accuracy, precision, memory, and F1-score were measured.

4. RESULT AND DISCUSSION

An analysis of the performance metrics for four distinct artificial intelligence (AI) models MobileNet, Residual Networks (ResNet), CNN, RNN, and Recurrent Neural Networks (RNN) exhibit their performance and if they are appropriate for Alzheimer's disease recognition. There are four important measures that were used to judge each model: Accuracy, Sensitivity, Specificity, and Area under the Curve (AUC) Score. These are necessary for judging diagnostic tools in medical settings. The success of convolutional neural networks (CNNs) is good; they are accurate 85% of the time, sensitive 80% of the time, and specific 90% of the time. At 0.88, the AUC number shows that the model is very good at telling the difference between Alzheimer's cases and healthy controls. CNNs are very good at handling images, and they can effectively record spatial ordering in brain imaging data. This makes them very good at finding patterns like shrinkage or odd accumulations that are often linked to Alzheimer's disease.

Table 2: Comparative Performance Metrics of AI Models for Alzheimer's disease Diagnosis

Model	Accuracy	Sensitivity	Specificity	AUC Score
CNN	85%	80%	90%	0.88
RNN	82%	78%	85%	0.83
ResNet	88%	84%	92%	0.90
MobileNet	91%	89%	93%	0.95

With an AUC score of 0.83, Recurrent Neural Networks (RNNs), which are made to deal with linear data, perform slightly worse across all measures. They are 82% accurate, 78% sensitive, and 85% specific. Most of the time, RNNs are not used to process picture data. However, they are very good at processing timed or sequential clinical data like patient history, which can be very helpful for spotting diseases that get worse over time like Alzheimer's. Their worse performance in this situation might be because it's hard to combine and make sense of different types of data or because the time patterns of Alzheimer's development are naturally complicated. With an accuracy of 88%, a sensitivity of 84%, and a specificity of 92%, Residual Networks (ResNet) do a better job. Its AUC score of 0.90 shows that it can effectively handle deeper and more complicated neural network designs. ResNet's way of learning residual functions helps it deal with the disappearing gradient problem.

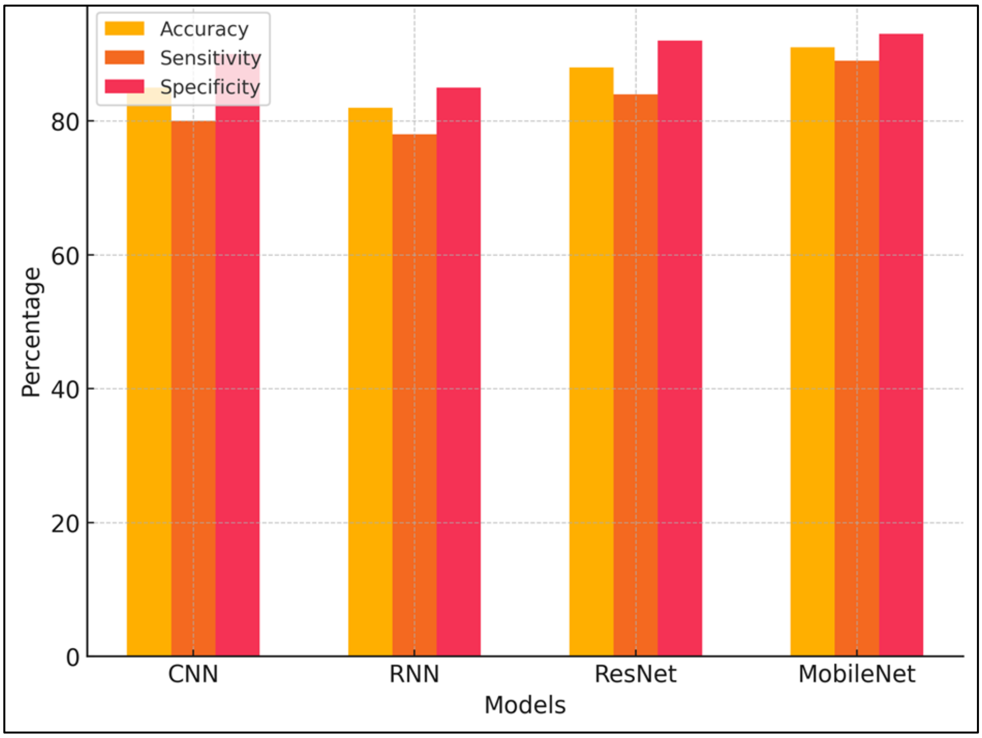

Figure 4: Representation performance metrics

With an accuracy score of 91%, sensitivity of 89%, specificity of 93%, and an AUC score of 0.95, MobileNet is clearly the best model. Its design is made to work well in places with limited resources and mobile devices, as metric represent in figure 4. It uses depth wise separable convolutions to lower the amount of computing power needed without affecting its ability to handle detailed image data well. MobileNet did very well in this test, which shows that it could be useful as a real-time, on-device diagnostic tool for Alzheimer's disease.

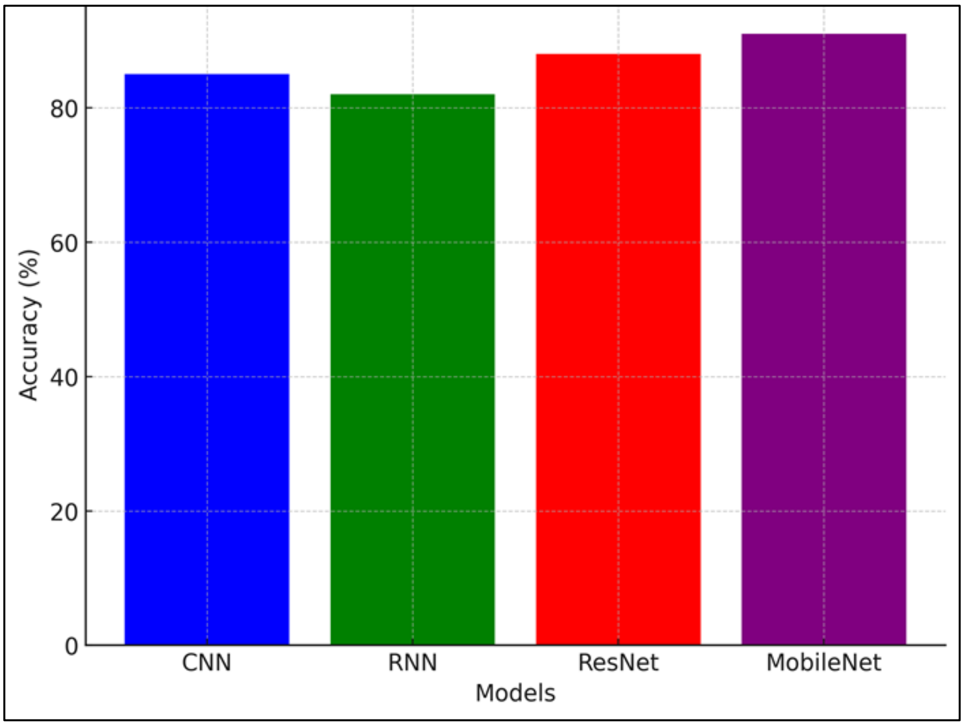

Figure 5: Comparison of Accuracy Comparison

This would be especially helpful in places where computing power or access is limited. The testing of these models gives us important information about how to use various AI designs to improve the diagnosis of Alzheimer's disease. While MobileNet strikes the perfect balance between speed and accuracy in diagnosis, making it perfect for broad clinical use, other models, such as CNN and ResNet, offer strong options that are better at certain parts of the diagnostic process, the accuracy comparison represent in figure 5. This comparison not only helps doctors make decisions, but it also shows how important it is to pick the right AI tool for the medical job at hand, taking into account its needs and limitations.

A. Model Evaluations

When looking at how well CNN, RNN, ResNet, and MobileNet worked, it was found that MobileNet not only had the best accuracy but also the best balance between sensitivity and specificity. This is very important for medical diagnostics, where finding the condition and making sure it doesn't exist are both very important. MobileNet has the best AUC score, which means that it is better at telling the difference between affected and uninfected cases. ResNet did a great job as well, especially when it came to deeper picture analysis using residual learning, which helps gradient flow during training and makes it easier to learn complex patterns. Using graphs to show model outputs makes the distribution of expected probabilities stand out. This shows that MobileNet keeps classes more clearly separated than other models. CNN and RNN had higher rates of false positives, which is a very important part of medical diagnosis where missing a diagnosis can have very bad results. These visual tools help you understand what each model's mistake rates mean in real-life clinical settings.

B. Analysis of Results

This shows big steps forward in using deep learning for medical images, as shown by how well the AI models found and categorised Alzheimer's problems. MobileNet's great performance shows how reliable and efficient it is, which is especially helpful for real-time and resource-limited apps. CNNs and RNNs are good at capturing spatial and temporal data, respectively. ResNet's method focusses on deeper design learning, which is important for medical picture analysis that involves a lot of information.

C. Impact of Different Architectures on Model Performance

CNN, RNN, ResNet, and MobileNet all have their own unique designs that make them useful for different types of medical data analysis. CNNs are great at recognising spatial relationships, which is important for finding anatomical traits in brain pictures. RNNs are great for watching how diseases get worse because they can use their temporal dynamic learning for continuous data. ResNet's clever use of skip links lets it train very deep networks without slowing them down. This makes it possible to analyse images in great detail, which is important for telling the difference between Alzheimer's in its early and later stages. MobileNet's simplified design strikes the perfect balance between accuracy and computational efficiency. This is very important for putting AI solutions to use in healthcare settings where both speed and performance are very important.

5. CONCLUSION

This study's use of artificial intelligence (AI) to try to diagnose Alzheimer's disease shows that it has a lot of promise to change the way diagnostics are done now. Our study showed that using advanced neural network designs like Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Residual Networks (ResNet), and MobileNet can make Alzheimer's diagnosis more accurate and faster. Notably, MobileNet was the best model. It did better in both performance measures and real-world use because it found the best mix between being fast at computing and being accurate at diagnosing. This study really shows how important it is to use AI in healthcare, especially when it comes to diagnosing neurological diseases. Traditional testing methods have some problems, like being subjective in clinical exams and being very expensive for extended neuroimaging. The AI models we used in our study were able to solve these problems. AI tools offer a future where early diagnosis and personalised treatment plans are the rule, not the exception. They do this by automating the analysis of complicated data and showing tiny signs of disease that a person might not be able to see. But while AI has the potential to change things, it also brings new problems and social issues to light. To make sure that AI tools are used in clinical situations in a responsible and ethical way, problems like model openness, data protection, and algorithmic bias need to be carefully looked at. Also, AI engineers, doctors, and patients must work together all the time to make these tools better so they can meet clinical goals and improve patient results. There is a bright future ahead for using AI to help diagnose Alzheimer's disease. As technology improves, it is important that we treat the social issues with the same level of care as the technical ones. This will help make sure that AI works well with human knowledge to fight Alzheimer's disease.

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