

CLOUD-INTEGRATED EARLY DETECTION OF ALZHEIMER'S DISEASE USING VGG-CAPSNET

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ABSTRACT

Alzheimer's disease (AD) progressively erodes the cognitive functions of memory and behavior, establishing it as one standardized dementia of nonelderly persons. Early diagnosis is essential so interventions can occur in time to slow the progression of the illness. Identifying structural damage by MRI scan type is important in diagnosing AD; however, the interpretation is manual-labour-intensive, subjective, and error-prone. Progressively, this paper generates a VGG-CapsNet model to detect early stages of Alzheimer's disease using the feature-extraction potential of VGGNet and the spatial hierarchy-preserving ability of Capsule Networks (CapsNets). The model is cloud-based, thus scalable and remotely accessible by healthcare providers. It provides an accurate and efficient diagnosis by using cloud deployment. This increases chances for continuous updates and refined predictions. VGGNet-CapsNet integration above with the cloud infrastructure encapsulates a scalable, efficient, and accurate early detection system for AD, hence helping the healthcare provider classify different stages of the disease.

Keywords: Alzheimer's Disease, MRI Scans, VGGNet, Capsule Networks, Deep Learning, Cloud Computing.

1. INTRODUCTION

Alzheimer's disease (AD) is indeed a neurodegenerative disorder that gradually influences cognitive functioning, memory, and behavior, and is among the commonest types of dementia, affecting individuals in their elderly years [1]. It extensively blights life, as the gradual loss in cognitive abilities makes it difficult for them to carry out even simple day-to-day activities, thus severely affecting their quality of life [2]. Therefore, an early diagnosis would ensure proper early interventions to halt the pace of deterioration and preserve some quality of life for the patient [3]. MRI scans may well be very useful in diagnosing Alzheimer's disease by observing patterns of brain atrophy and other structural aberrations characteristic of the disease [4] in a timely manner. However, it may often be said to be subjective, given its interpretation demands expert eyes and extensive knowledge [5]. Besides, manual analysis is time-consuming and adds appreciably to human error because revealing even exceedingly subtle changes in the early stage of the disease is a daunting task [6]. Hence there is an increasing need for an automated and fast tool able to increase

the level of accuracy and speed of detection of Alzheimer's diseases from MRI images [7]. These automated tools should reduce clinical diagnostic errors while increasing efficiency in the clinical workflow and providing better overall care to patients [8]. In response to the said challenges, deep learning techniques, particularly VGGNet, have been increasingly employed for medical imaging tasks, which include the detection of Alzheimer's disease [9]. VGGNet is a widely accepted convolutional neural network (CNN) that performs extremely well at extracting features by characterizing subtle patterns in very complicated images [10]. However, while VGGNet is known to extract features, it somewhat neglects the spatial relationships between parts of the image, which properly account for the understanding of structural changes in the brain due to Alzheimer's disease [11]. To alleviate these shortcomings, CapsNets have been analysed as a potent alternative for capturing the spatial hierarchies and part-whole relationships within an image [12].

CapsNets allow for understanding and retaining spatial relationships between different brain regions important for Alzheimer reconnaissance [13]. The construct under VGG-CapsNet merges VGGNet and CapsNet, exploiting VGGNet for obtaining high-level features while using CapsNet for preserving spatial relationships. In this way, VGG-CapsNet is, therefore, a more precise and robust tool for classifying Alzheimer's disease [14]. The worked model is cloud-based, thus favouring scalability, access, and usage by healthcare personnel in different places [15]. The system therefore makes an effective and user-friendly instrument in helping doctors classify Alzheimer's disease into Mildly Demented, Moderately Demented, Non-Demented, Very Mildly Demented, etc., with cloud computing [16]. Further deployment will help the development of large datasets, allowing the results to be fast and reliable for early detection of Alzheimer's disease [17]. Additionally, cloud deployment will guarantee future updates and refinements of the model in order to respond to new data and aid in improving diagnostic performance over time [18]. In this paper, the VGG-CapsNet approach is presented as a possible solution toward the diagnosis of Alzheimer in tackling the problems of early detection and presents an automated, scalable, and efficient means of assisting the healthcare provider [19]. Through VGGNet and Capsule Networks, clustering into cloud computing intends the routing of vastly possible routings for enhancing detection of Alzheimer's disease in accuracy and efficiency terms [20]. The integration of all the aforementioned technologies makes it possible for the proposed technique to be a great leap in the medical imaging and diagnosis of Alzheimer, with more accurate and clinically usable availabilities [21]. The potentiality of the system to improve diagnostic workflows and cut down diagnostic errors is a big jump ahead in early Alzheimer's disease diagnosis. [22] This research emphasizes the necessity of integrating deep-learning models with the cloud infrastructure for efficient delivery of health care to ensure that more patients benefit from early Alzheimer's detection [23].

1.1. Objective

- Assess the effectiveness of the combination of VGGNet for feature extraction with Capsule Networks for classification in detecting Alzheimer's disease from MRI scans.
- Create a cloud setup that guarantees accessibility and scalability of the Alzheimer's disease detection system in favour of healthcare providers.
- Evaluate the performance of the proposed VGG-CapsNet model in the classification of the different stages of Alzheimer's disease, including Mild Demented, Moderate Demented, Non-Demented, and Very Mild Demented.

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- Enhance diagnostic detection accuracy for Alzheimer's disease by automating MRI scan-based analysis to minimize human error and fasten the results.
 - The establishment of cloud deployment will enable continuous updating and improvement in model development in order to maintain the currency of its diagnostic effectiveness.
 - Evaluation of the model in terms of critical metrics, accuracy, precision, recall, F1-score, and AUC will be done to understand its usefulness for application in the medical field.

2. LITERATURE SURVEY

Deep learning application in medical imaging has tremendous potential to diagnose and classify images of Alzheimer's diseases through CNNs [24]. Application of those widely in MRI scans helped extract high-level features indicative of Alzheimer's disease [25]. The limitations of CNNs come from the fact that they pose a challenge for creating spatial hierarchies and part-whole relationships among different regions in the brain, which is critical for detecting very subtle changes in structures of the brain, mainly at the early stage of the disease [26]. All these unrealized challenges have given rise to the development of alternative architectures that could build better complex spatial relations [27].

Capsule Networks (CapsNets) have been proposed to overcome the limitations of CNNs with respect to spatial hierarchy [28]. CapsNets, therefore, act to preserve the spatial relationship of parts of an object and are well suited for situations in which understanding the relationships among various regions of an image is critical [29]. These properties of CapsNets have shown promise in medical imaging, where structural and positional properties of the features are essential for accurate diagnosis [30]. For image classification tasks, CapsNets perform better than CNNs, especially in pattern recognition, where the spatial arrangement of features plays an important role, for example in brain MRI scans to recognize Alzheimer's disease [31]. Since then, CapsNets have been applied in a number of domains in medical imaging, including tumour classification and brain disorders, where preservation of spatial relationships between regions is key to accurate diagnosis [32].

VGGNet is comparatively a deep convolutional neural network that can be described as simple but deep, and it is used for the extraction of hierarchical features from images [33]. VGGNet has been rather widely used for feature extraction in the context of Alzheimer's disease, as that network was efficient in capturing complex patterns from MRI scans [34]. The deep architecture of the network extracts low-level and high-level features from images, which can help classify different stages of Alzheimer's disease [35]. However, while VGGNet is really good for feature extraction, its limitation is that it does not preserve spatial hierarchies well in fine-grained structural alterations of the brain with respect to the early stages of Alzheimer's disease [36]. In this case, the work led to combining this feature extraction approach of VGGNet with advanced architectures like Capsule Networks to gain spatial relevance in the detection process [37].

VGGNet has recently been merged with CapsNets in their mutual strengths [38] and succeeded by claim. The hybrid uses VGGNet for feature extraction and CapsNets for classification to deliver more excellent performance than the use of either model alone [39]. The benefit, however, lies in the detailed extraction of information from the available dataset using VGGNet and keeping the spatial relationships and part-whole hierarchies in images which makes it more robust for the classification of Alzheimer's disease using CapsNets [40]. It has shown a better classification accuracy and has been very successfully applied in medical image analysis, specifically in the

brain where these spatial relationships are significant for diagnosis [41].

Combining machine learning systems, including deep learning designs such as VGG-CapsNet, with the cloud becomes increasingly essential day by day in the health industry [42]. As its name implies, the cloud has much to provide in a very easy way when compared to much in terms of scalability, access, and groups' processing without necessarily needing to travel-n putting itself into the perfect location for health-related applications [43]. Cloud infrastructure enables healthcare professionals to access diagnostic tools remotely, resulting in efficient and faster diagnoses [44]. The result is also that the model can accommodate very large datasets-shared resource-efficient processing of MRI scans from multiple patients [45]. In addition, cloud implementation allows the model to be updated and trained repeatedly upon acquiring new data, providing improved diagnosis thereafter [46].

Recent advancements in deep learning have explored the integration of attention mechanisms with Capsule Networks to enhance feature representation and spatial understanding in medical images. Attention-enhanced CapsNets have shown improved performance by focusing on the most relevant regions of brain MRI scans. This approach increases sensitivity in detecting early Alzheimer's-related changes [47]. Such hybrid attention-CapsNet architectures address the limitation of vanilla CapsNets in processing complex neuroimaging data. They enable better discrimination among subtle stages of cognitive decline [48]. These methods have been demonstrated to improve diagnostic accuracy compared to traditional CapsNet models [49].

In parallel, transfer learning approaches leveraging pretrained models like VGGNet on large-scale natural image datasets have demonstrated considerable improvements when fine-tuned on Alzheimer's MRI datasets [50]. This method reduces training time and computational costs. It also increases accuracy by utilizing rich hierarchical features learned from diverse image domains [51]. Studies combining transfer learning with CapsNet classification further confirm that feature reuse significantly boosts early-stage Alzheimer's detection [52]. This is especially true in scenarios with limited annotated medical data [53]. Transfer learning has therefore become an essential technique in Alzheimer's disease image analysis [54].

Moreover, the role of multimodal neuroimaging data fusion has gained traction in recent years. Researchers have integrated MRI with other modalities such as PET, fMRI, and clinical data to improve Alzheimer's disease diagnosis [55]. Deep learning frameworks employing VGGNet and CapsNet backbones in multimodal architectures show enhanced robustness and generalizability [56]. These models capture complementary pathological markers across different imaging types [57]. Multimodal systems outperform unimodal approaches by providing a more comprehensive view of disease progression [58]. This facilitates more accurate stage classification of Alzheimer's disease [59]. The integration of multiple data sources is proving crucial for early and reliable diagnosis [60].

Finally, the growing adoption of cloud-based AI platforms for healthcare delivery has catalyzed innovations in real-time model deployment and collaborative learning for Alzheimer's detection [61]. Federated learning on cloud infrastructure enables decentralized training of VGG-CapsNet models on patient data from multiple hospitals [62]. This training occurs without compromising patient privacy [63]. Such collaborative paradigms lead to continuous improvement of diagnostic models [64]. They also accelerate clinical translation while complying with data security regulations [65]. Additionally, cloud-enabled visualization tools assist clinicians in interpreting model outputs [66]. These tools enhance trust and adoption of AI in practical medical settings [67].

Cloud infrastructures are thus key enablers for scalable and efficient Alzheimer's diagnostic systems [68]. They support large-scale data sharing and resource-efficient processing [69]. These advances mark a significant step toward widespread clinical use of AI for early detection of Alzheimer's disease [70]. They enable continuous learning from new patient data, which helps improve model accuracy over time [71]. Moreover, integrating AI tools into existing healthcare workflows can reduce the workload on medical professionals [72].

2.1 Problem Statement

Cognitive impairment, memory loss, or change in behavior is a progressive degenerative disorder described as Alzheimer's disease (AD). Early and accurate detection of the disease would allow the timely intervention, with the objective of slowing down the progression of the disease further [73]. The major diagnostic tools in detecting AD currently include magnetic resonance imaging (MRI) scans, all of which require expert interpretation that is often subjective and time-consuming [74]. Diagnosis continues to rely heavily on manual interpretation, an approach that result in inconsistent and delayed identification of the disease in the early stage. Thus, there is an urgent need for an automated and effective system that can accurately analyse MRI scans, classify all stages of Alzheimer's disease, and provide access to all health facilities [75]. This research proposes an early detection model of Alzheimer's disease using VGG-CapsNet to enhance the accuracy or scalability of diagnostics with a cloud-based infrastructure built on deep learning concepts [76].

Despite advancements in imaging technologies and machine learning, current diagnostic approaches for Alzheimer's disease still face significant challenges in terms of scalability and generalizability across diverse populations [77]. Many automated systems fail to integrate seamlessly with existing healthcare workflows, limiting their practical utility and accessibility in under-resourced settings [78]. Moreover, variability in MRI scan quality, patient demographics, and disease presentation often hampers the robustness of diagnostic models, necessitating continual adaptation and validation [79]. The lack of centralized and scalable platforms restricts real-time collaboration and data sharing among clinicians, impeding the rapid evolution of diagnostic tools. Cloud-based frameworks offer a promising solution by enabling dynamic model updates, federated learning, and remote accessibility, which are critical for addressing these gaps [80]. Therefore, it is imperative to develop systems that not only enhance accuracy but also ensure broad accessibility and adaptability in clinical environments to improve early Alzheimer's detection outcomes.

3. PROPOSED METHDOLOGY

Figure 1 provides insight into the complete workflow for Alzheimer's disease classification using the VGG-CapsNet model. The workflow starts with Data Collection, which is the process through which MRI images of patients with different stages of Alzheimer's are taken. The collected data is then Preprocessed, which includes steps such as image augmentation and normalization for getting the data ready for training. After this, features are extracted using VGGNet, during which relevant features from the MRI images are extracted. The extracted features are then fed to the Capsule Networks for classification, in which the network then outputs four-class predictions: Mildly Demented, Moderately Demented, Non-Demented, and Very Mildly Demented. Consequently, the cloud deployment of the model makes it accessible and scalable, while performance metrics

evaluate its accuracy and efficiency in the classification process.

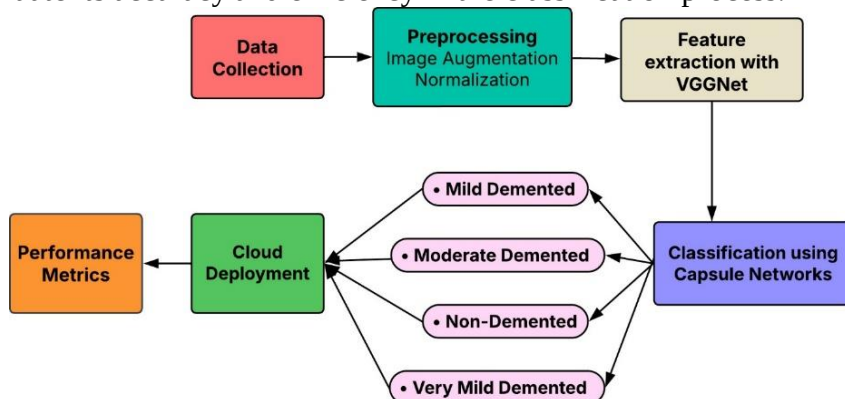


Figure 1: Alzheimer's Classification Using VGG-CapsNet

3.1 Data Collection

The data collection process for Alzheimer's disease detection involves collecting a comprehensive dataset of MRI images that represent different stages of Alzheimer's disease. In this case, the set contains images of the Alzheimer's Disease Neuroimaging Initiative (ADNI) or similar sources in four classes: Mild Demented, Moderate Demented, Non-Demented, and Very Mild Dement. Edmore generally, the MRI data sets are generally referred to by two different folders: Original Folder, which contains the MRI data set images, primarily for validating or testing, and Augmented Folder, which includes the images obtained by using different augmentation techniques (rotation, flipping, scaling, etc.): thereby increasing training data variability and size. Data are utilized to train deep learning models to detect and classify stages of Alzheimer's disease from MRI brain scans. The model is ensured to be robust, generalizable, and perform well on unseen data using augmented and original images.

3.2 Preprocessing

Preprocessing Data Consistency prepares entrance MRI images into the deep learning model after performing pivotal steps that lead to improved performance of models. Firstly resize any image taken by a standard dimension, which is typically 224x224 pixel images to fit the input requirement of the VGGNet model. Image augmentation has several techniques, including rotating, flipping, and scaling the image, for artificial enlargement and increased diversity in the dataset to improve the generalization of a model. Then, images are normalized: pixel values are adjusted to a certain standard range (e.g., [0, 1] or [-1, 1]), so stabilization in learning processes is achieved whereby converging during training is improved. The augmented images would be used primarily for training the dataset, whereas the reserved original images would be utilized for validating and testing the model's performance. Therefore, preprocessing guarantees the data clean, standardized, and ready for efficient training and evaluating models.

3.2.1 Image Augmentation

Image augmentation is a technique augmenting amount of data by the application of transformations to the original images. This helps improve the generalization of a model by

exposing it to different variations of the images, thereby making it more robust to real-world variations in the data. Popular augmentation techniques involve rotation, flipping, scaling, translation, and brightness adjustment, among others. The transformations can be mathematically expressed in eqn1:

$$I_{\text{aug}} = T(I) \quad (1)$$

In this equation, I_{aug} is the augmented image, I is the original image, and T is the transformation function that will include transformation operators such as rotation T_{rotate} , scaling T_{scale} , flipping T_{flip} , etc. In other words, a suitable rotation transformation can be written in eqn2:

$$T_{\text{rotate}}(I) = R(\theta) \cdot I \quad (2)$$

with $R(\theta)$ being a rotation matrix represented according to a counter clockwise rotation of angle θ for image I . The use of these augmentations introduces variability in the dataset, which enhances the model's ability to discern those patterns with different input variations.

3.2.2 Normalization

Normalization is a sort of preprocessing method applied to rescale the image pixel values to some expected range, generally $[0, 1]$ or $[-1, 1]$, so that the convergence of the deep learning model is enhanced. This implies that now all input features (pixel values) are on a similar scale, accelerating the learning process because no one feature can dominate the training. Normalization can therefore be defined mathematically with the following eqn3:

$$I_{\text{norm}} = \frac{I - \mu}{\sigma} \quad (3)$$

Where here I_{norm} is the normalized image, I is the original pixel value, μ is the mean of the pixel values considered for the dataset, and σ is the standard deviation of the pixel values. This scheme makes the pixel values standardized with a mean of 0 and a standard deviation of 1 so that the model will treat all features with equal importance. Alternatively, in some cases, normalization may be performed simply by scaling the pixel values to $[0,1]$ using:

$$I_{\text{norm}} = \frac{I}{255} \quad (4)$$

where 255 is the maximum pixel value in an 8-bit image. This gives uniformity to the pixel values and is helpful for performance and stability.

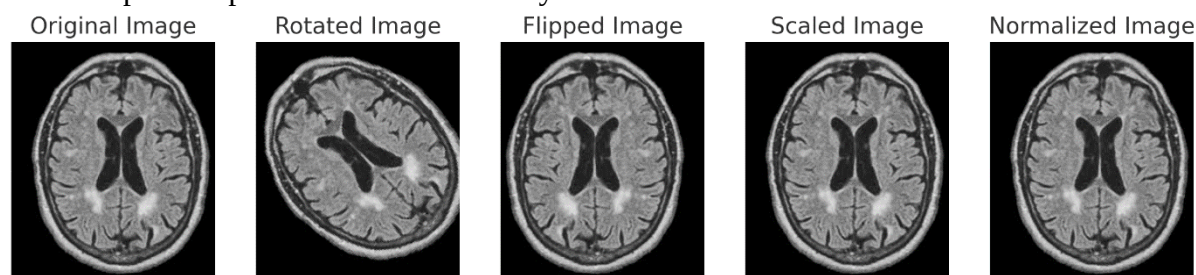


Figure 2: MRI Image Preprocessing Techniques for Alzheimer's Disease Detection

3.3 Feature Extraction Using VGGNet

A feature extraction using VGGNet refers to the automatic extraction of high-level features that

are meaningful for any input image using a pre-trained instance of the VGGNet model. VGGNet is a Convolutional Neural Network (CNN) whereby the input image first passes through the convolutional layers, then through several max-pooling layers that step-by-step take out progressively more complex features from the image. The outputs from the feature extractors represent the extracted features on which the fully connected layers perform their own processing and classification. Pretty much anything could be the features-some basic edges, patterns, and textures, for instance-more complex patterns of shapes and objects, etc. Mathematical expression of feature extraction:

$$F = W_n \cdot (W_{n-1} \cdot (\dots (W_1 \cdot I + b_1) + b_2) \dots) + b_n \quad (5)$$

Where: F' is the final feature map or output of the VGGNet model, I is the input image, $W_1, W_2, \dots, W_n$ are the learned weight matrices for each convolutional layer, $b_1, b_2, \dots, b_n$ are the corresponding bias terms for each layer, represents the convolution operation applied at each layer. The convolution layers of VGGNet decrease the spatial dimension of the image while increasing the depth of the feature maps so that early layers may capture the simpler features such as rough edges, while deeper layers learn to capture complex patterns. Such features may then be used for classification or handed-off to more layers for further processing.

3.4 Classification Using Capsule Networks

Figure 3 shows a layout of Capsule Networks (CapsNet) for classifying Alzheimer's disease based on MRI images. The architecture begins with convolutional layers to extract the basic features from the MRI scan such as edges and textures. Afterward, the ReLU activation is applied to introduce non-linearity. Instead of pooling layers, CapsNets have capsule layers composed of groups of neurons that learn spatial hierarchies and relationships between parts of the image. These capsules are connected through dynamic routing, i.e., capsules pass information among themselves according to an agreement, thus enhancing the capability to capture complex spatial patterns. After capsules extract image features from the MRI scan, final classification is performed by the model, where data is passed onto fully connected layers producing predictions of the Alzheimer disease stages: Mild Demented, Moderate Demented, Non-Demented, and Very Mild Demented. This architecture allows the model to better maintain spatial relationships and part-whole hierarchies in the image.

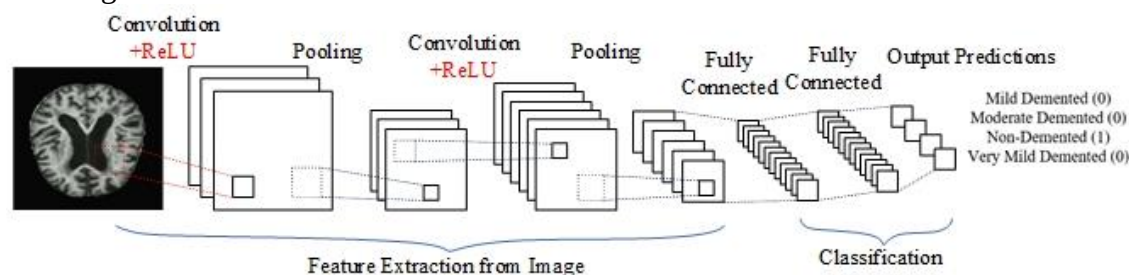


Figure 3: Capsule Network

3.4.1 Dynamic Routing:

Dynamic Routing is one of the major elements of Capsule Networks (CapsNets) with the responsibility of maintaining relationships and spatial hierarchies between parts of an image.

Unlike traditional neural networks, which exist in theoretically endless space due to the operational properties of their pooling layers, dynamic routing keeps these critical spatial relationships alive by performing a routing mechanism dependent on agreement between lower-level capsules and higher-level capsules. Thus, it is allowed for networks to comprehend and keep even very complex spatial relationships relative to the relationship of the different parts that make up an object in an image. The routing-by-agreement illustrates dynamic routing and provides for the iterative updating of the coupling coefficients between capsules, which are given in the equations for dynamic routing.

$$v_j = \sum_i c_{ij} u_i \quad (6)$$

Where: v_j is the output vector of the higher-level capsule j , u_i is the output vector of the lower-level capsule i , c_{ij} is the coupling coefficient that determines how much influence capsule i has on capsule j . This coefficient is updated during the routing process to reflect the agreement between the capsules. Updated in tandem, the coupling coefficients c_{ij} represent the surety with which the predicted output vector (u_i) of lower capsules corresponds with the actual output of higher capsules (v_j):

$$c_{ij} \leftarrow c_{ij} + u_i \cdot v_j \quad (7)$$

The performance of the output prediction by their outputs on a current date, $u_i \cdot v_j$, calculates the alignment between the output prediction and the current output. This process is carried out iteratively until the convergence of coupling coefficients has been achieved. Thus, higher-level capsules can learn the accurate representations of spatial relationships on a complex level and, thereby, improve the model's ability to learn part-whole and hierarchical patterns underlying image data.

3.4.2 Final Classification

The capsules will then be used for the final classification stage in a Capsule Network after processing and encoding the spatial relationships and features. It is then passed on to the classification layer as the final output of that Capsule Network for classification (Mild Demented, Moderate Demented, Non-Demented, or Very Mild Demented). The classification part usually involves performing a last vote from the capsules and picking the class with the highest confidence. the class of the input image has to be determined from capsule output. Right after dynamic routing, each capsule produces an output vector v_j for every class j , wherein the length of that vector, $\|v_j\|$, indicates the confidence that the image is allocated to that class. Classification is undertaken using the SoftMax function for the purpose of converting the length of the output vector into a probability and can be expressed as:

$$P(y = j | I) = \frac{e^{\|v_j\|}}{\sum_k e^{\|v_k\|}} \quad (8)$$

Where: $P(y = j | I)$ is the probability that the image I belongs to class j , and the denominator normalizes the probabilities across all possible classes.

$$\hat{y} = \arg \max_j P(y = j | I) \quad (9)$$

This way, the model produces the entry profession class name (e.g., Mild Demented, Moderate Demented, Non-Demented, Very Mild Demented) with maximum confidence via learned spatial relations.

3.5 Cloud Integration

Cloud Deployment entails how to deploy the trained Alzheimer's disease classification model to a cloud platform, like Microsoft Azure, AWS, or Google Cloud, so that it can be easily accessible and scalable. After deployment, health practitioners can upload MRI images over a web interface, and the model is going to process the images into different stages of Alzheimer's disease classification (e.g., Mild Demented, Moderate Demented, Non-Demented, Very Mild Demented). Cloud deployment will allow the system to be accessed from different locations and gives an advantage for efficient and widespread use, without requiring localized infrastructure. It also allows the model to be improved and updated over time, manage large datasets, and provide reliability and availability covering all these aspects, thus rendering it a very effective solution for the healthcare-provider needing timely diagnoses based on MRI scans.

3. RESULT AND DISCUSSION

Figure 4 compares the performance metrics of a classification model with respect to Accuracy, Precision, Recall, and F1 Score. The model Accuracy of 98.68% indicates the highest level of correctness in the model predictions overall. Precision, which determines how many of the positive instances among the predicted ones are actually positive, is equally high at 97.87%. This indicates that the model has a very high level of confidence in predicting positives. Recall that measures the ability of the model to identify true positive cases stands at 97.57%, indicating very respectable performance in identifying the relevant instances. Of note is the F1 Score, which combines precision and recall, is a bit lower at 97.11%, indicating very high overall performance. The color-coded bars display the model performance for easier comparison against each of the other metrics.

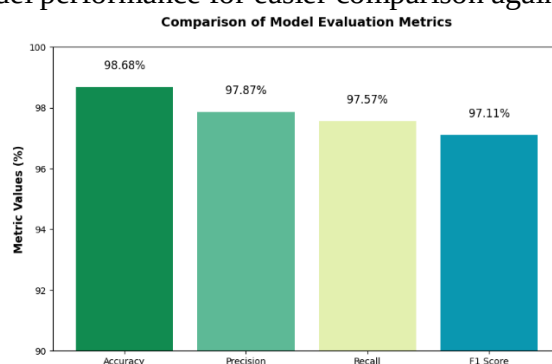


Figure 4: Performance Metrics

Figure 5 depicts the performance of a classification model for predicting the stages of Alzheimer's disease. The matrix categorizes four parts: Mild Demented, Moderate Demented, Non-Demented, and Very Mild Demented. The diagonal elements are basically correct predictions in each of the categories, with correct predictions being the highest for Mild Demented (1465), followed by non-

Demented (1286), Very Mild Demented (1193), and Moderate Demented (1377). The off-diagonal elements represent where there was misclassification, wherein predictions for one class were assigned to another. The model performs fairly well at the identification of Mild Demented and Very Mild Demented stages indeed, while there are frequent misclassifications in contrasting the Moderate Demented and Non-Demented categories. The confusion matrix allows for assessing the model's performance in distinguishing the stages and also throws light on improvement opportunities.

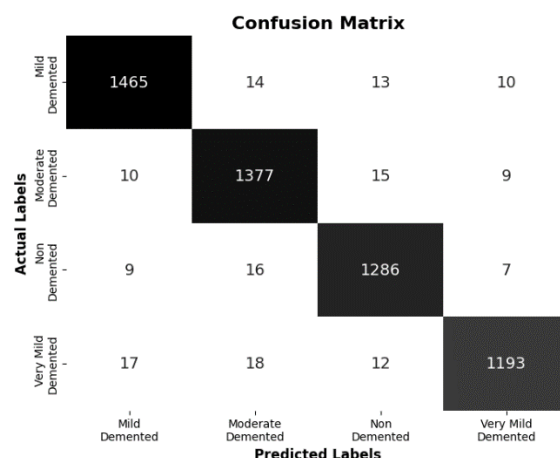


Figure 5: Confusion Matrix

Figure 6 assume that we have this ROC Curve for Multi-Class Classification indicating how the model performed in classifying the stages (Mild Demented, Moderate Demented, Non-Demented, and Very Mild Demented) of Alzheimer's disease. Each stage curve would provide information regarding TPR and FPR concerning that specific stage of disease progression. The performance of the random classifier is depicted by the diagonal dotted line. These final four curves (one for each stage) have an AUC score of 0.98, which implies a high level of performance by the model in differentiating one stage of Alzheimer's disease from another stage. The cut-off points of the curves are also displayed nearer the top-left corner of the ideal case for a good classification, which signifies better classification accuracy.

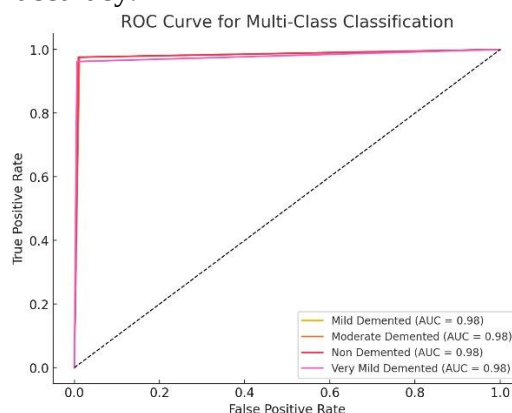


Figure 6: ROC Curve

3. CONCLUSION

The fusion of VGGNet and CapsNets in the VGG-CapsNet model promotes a powerful and accurate approach towards the early diagnosis of Alzheimer's disease. VGGNet extracts high-level features from magnetic resonance images (MRIs), while Capsnets are capable of maintaining the spatial relationship which is highly important in detecting subtle changes in brain structures, particularly in the early stages of Alzheimer's. The cloud-based deployment also improves access and scalability of the system across multiple clinical sites and keeps it growing by the updates. The system proposed can help a considerable amount in reducing the inaccuracies in diagnosis, improving efficient diagnosis, and giving health professionals a reliable tool for classifying stages of Alzheimer's disease and much more in helping toward early detection in Alzheimer's care. Thus, further deep learning progress combined with cloud technology will enhance the system's capability, marking a new-age dimension for Alzheimer's diagnosis and treatment.

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