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Application of Machine Learning for Dementia Classification through MRI Images using Vertex AI on Google Cloud Services

Tiara Disti Rinanda[1], Aldo Lovely Arief Suyoso[2], Hendro Margono[3,*]

[1] Postgraduate School, Master of Human Resources Development, Universitas Airlangga, Surabaya, Indonesia
[2] Human Resource Development, Universitas Airlangga, Surabaya, Indonesia
[3] Information and Library Department of Human Resource Development, Universitas Airlangga, Surabaya, Indonesia
Email: [1]tiara.disti.rinanda-2023@pasca.unair.ac.id, [2] aldoelarief@gmail.com , [3,*]hendro.margono@fisip.unair.ac.id
Corresponding author email: tiara.disti.rinanda-2023@pasca.unair.ac.id
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Abstract−Alzheimer's dementia remains a significant global health challenge, particularly in resource-limited countries where early and accurate diagnosis is critical to reducing morbidity and mortality rates. This study leverages machine learning, specifically Convolutional Neural Networks (CNN), to develop a reliable model for detecting the severity of dementia using brain MRI images. A dataset consisting of 1,561 MRI images across four categories (Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented) was sourced from Kaggle. Techniques such as AutoML, which automates model parameter optimization, and image segmentation, focusing on critical brain features, were used to enhance accuracy. The model, trained using Vertex AI on Google Cloud, achieved a precision rate of 93.5% and a consistent classification accuracy of 92%–93% across all dementia categories. These findings underscore the potential of CNNs in improving dementia detection even in resource-constrained settings. While challenges such as data sensitivity and computational demands were acknowledged, future work could explore federated learning for secure data handling and optimize computational workflows to address these issues. This scalable and adaptable model not only improves diagnosis accuracy but also has the potential to revolutionize early dementia detection in under-resourced healthcare systems, reducing diagnosis time and enabling timely interventions. By utilizing advanced machine learning techniques, this research highlights the transformative role of technology in public health efforts to combat Alzheimer's disease globally.

Keyword: Alzheimer; MRI; CNN; Vertex AI; Google Cloud

1. INTRODUCTION

Alzheimer’s disease is the leading cause of dementia, primarily affecting the brain’s nervous system in elderly individuals. This progressive and irreversible condition results in significant cognitive decline, including memory loss, communication difficulties, and behavioral changes, ultimately impairing patients' ability to carry out daily activities [1] [2]. The prevalence of Alzheimer’s is rising alarmingly, with the 2018 World Alzheimer Report estimating approximately 50 million cases worldwide, projected to triple by 2050. In Indonesia alone, over one million people were affected in 2013, and this number is expected to double by 2030 [3].

Early diagnosis of Alzheimer’s is crucial, as it enables timely interventions that can significantly slow cognitive decline, improve patient outcomes, and reduce long-term healthcare costs. However, traditional diagnostic methods face challenges such as high costs, resource limitations, and difficulties in distinguishing the early stages of the disease, which often exhibit subtle symptoms. Magnetic Resonance Imaging (MRI) has become a primary tool for diagnosis due to its ability to produce detailed images of brain structures. Nonetheless, current approaches are hindered by data diversity and computational inefficiencies, limiting their broader application in clinical settings [4] [5].

In recent years, studies have integrated machine learning techniques with MRI imaging to enhance the accuracy and automation of Alzheimer’s detection. One prominent area of research involves MRI segmentation algorithms designed to identify critical patterns in brain structures. For instance, Yamanakkanavar et al. [4] conducted a survey on MRI segmentation and classification using deep learning for Alzheimer’s diagnosis. This study highlighted the challenges in developing algorithms capable of detecting subtle changes in brain structures, such as the hippocampus, which are crucial for early detection. Another study by Nazil et al. [5] proposed a Convolutional Neural Network (CNN) method for classifying the severity of Alzheimer’s dementia using MRI images. Using a dataset categorized into four groups (Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented), their model achieved an accuracy of up to 90%. However, the study was limited by the dataset size, raising concerns about the generalizability of its findings across diverse populations. Sorour et al. [6] advanced this approach by leveraging transfer learning-based deep learning techniques to classify Alzheimer’s MRI data. This study demonstrated that transfer learning could overcome data limitations by utilizing pre-trained features from large datasets. The findings suggest that transfer learning is a promising solution for improving accuracy in resource-constrained scenarios.

In addition, Gustian et al. [7] explored the use of Google Cloud Vertex AI for training image classification models. Their research showcased how cloud platform integration could significantly accelerate the training and testing processes of machine learning models, particularly when handling large-scale data with high complexity. By utilizing cloud computing, challenges related to local infrastructure were mitigated, enabling the implementation of these technologies in resource-limited environments.

This study aims to address several limitations of previous research by integrating image segmentation methods, CNNs, and cloud computing through the Google Cloud Vertex AI platform. Utilizing an MRI dataset with four dementia categories, this research develops a model that not only achieves high classification accuracy but is also

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scalable for clinical applications. The cloud-based approach allows for the deployment of this model in hospitals or clinics, particularly in developing countries, supporting early diagnosis and improving patient outcomes.

Thus, this research significantly contributes to the literature by offering an innovative solution that integrates machine learning and cloud computing for Alzheimer's diagnosis. It also promotes the broader adoption of health technologies, particularly in resource-constrained regions, enhancing early detection and management of Alzheimer's disease on a global scale.

2. RESEARCH METHODOLOGY

The following Figure 1 shows the stages of the research carried out.

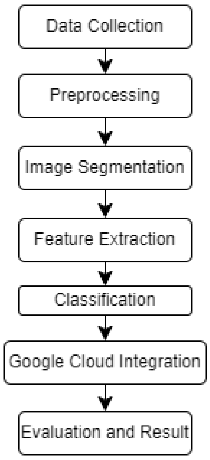

Figure 1 Workflow Research

2.1 Dataset Description

The dataset used in this study consists of MRI images taken from the Kaggle platform. This dataset includes images of patients with varying levels of dementia severity: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. These images were selected for their ability to demonstrate significant visual differences between different dementia severity levels, which are important for training and evaluating the image classification model[7].

In total, the dataset consists of 1,561 images divided into three main groups: Training Set, Validation Set, and Test Set. This division was made to ensure that the model trained can recognize patterns from the training data but is also tested on unseen data and validated to measure the model's generalization capability[8].

a. Training Set: Consists of 1,248 images across four dementia categories. These images are used to train the model to recognize important patterns that distinguish between the levels of dementia severity.
b. Validation Set: Consists of 157 images used during the training process to measure the model's performance on data not included in the training set. This set helps in adjusting the model parameters to optimize its performance.
c. Test Set: Consists of 156 images used after the model training is complete to test its ability to classify images with high accuracy. This test set includes randomly selected images from the four dementia categories to ensure that the model provides consistent and reliable results.

Figure 2 Dataset MRI Alzheimer

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The Figure 2 in this dataset display various differences in terms of patient positioning, imaging angles, and image quality, which are designed to challenge the model's ability to identify the severity of dementia. Additionally, each image has been manually labeled to ensure that the assigned dementia categories are accurate and reliable as a basis for model training. With a balanced division between the training set, validation set, and test set, this study ensures that the developed model is not only well-trained but also has the ability to generalize on new data, making it reliable for clinical applications or further research.

2.2 Data Processing

The data processing procedure in this study involves several key steps aimed at preparing the MRI images for use in training the dementia classification model. Each data processing step is carefully executed to ensure that the model receives optimal and relevant input to improve classification accuracy[9].

a. Data Collection: MRI image data was downloaded from the Kaggle platform, encompassing the four dementia severity categories: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. These images were uploaded to Google Cloud Storage for easy storage and access during the data processing and model training phases.
b. Preprocessing: Preprocessing was carried out to ensure that each image had consistent format and quality before being used for model training. This included:
    1. Resizing: Each image was resized to a standard dimension suitable for the model's input requirements. This ensures all images have uniform size, minimizing irrelevant variations that could impact model training.
    2. Normalization: Images were normalized to reduce irrelevant pixel intensity variations. Normalization is performed by transforming the image pixel values to the same range, typically between 0 and 1, which helps the model identify important patterns without being affected by variations in image brightness or contrast.
    3. Data Augmentation: To increase the diversity of training data and reduce the risk of overfitting, data augmentation techniques such as rotation, horizontal flipping, and scaling were applied. These techniques help the model learn to recognize key features from various perspectives and scenarios.
c. Labeling: Each image in the dataset was manually labeled according to the dementia severity level shown. Accurate labeling is crucial since these labels will be used by the model to learn how to classify images. The labeling process was conducted on Google Cloud Platform, where the uploaded images were organized and labeled according to their respective categories.
d. Image Segmentation: Image segmentation was performed to focus the model on the important areas of the MRI image relevant to dementia diagnosis. In this study, segmentation algorithms were used to divide the images into several segments based on texture and intensity similarities. This allows the model to focus more on key features, such as brain structure changes related to dementia, rather than irrelevant visual noise.
e. Feature Extraction: After image segmentation, the next step was feature extraction, where important characteristics of the image were identified and extracted for use in model training. Techniques such as Histogram of Oriented Gradients (HOG) and Scale-Invariant Feature Transform (SIFT) were used to capture information about shape, texture, and orientation of key elements in the images. These features were then inputted into the model to assist in the classification process.

This systematic and structured data processing procedure ensures that the model receives high-quality data, ready for training, and thus improves the accuracy and reliability of dementia image classification results[10].

2.3 Model Selection: Convolutional Neural Network (CNN)

The selection and training of the model are crucial stages in this research, where the main objective is to build a classification model capable of recognizing and distinguishing the severity of dementia based on MRI images. This process involves several key steps, starting from model selection to training and optimization using Google Cloud's Vertex AI.

a. CNN Model Selection: This study uses an image classification approach with a Single-Label Image Classification model provided by Vertex AI on Google Cloud. This model was chosen because of its ability to categorize MRI images into one of four predetermined classes: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. The selection of this model was based on the need to identify the most appropriate category based on the visual patterns detected in MRI images[11].
b. Training Configuration: After selecting the model, the training configuration was carefully conducted to ensure that the model could learn from the provided data. Several important parameters were configured, including:
    1. Training Algorithm: The algorithm used to train the model was chosen based on its performance in medical image classification. This algorithm is responsible for optimizing the model's weights during training so that the model can recognize relevant patterns in the data.
    2. Learning Rate: The learning rate was set to control how fast the model learns from the data. The chosen learning rate ensures that the model converges quickly while remaining stable, avoiding overshooting or underfitting.
    3. Epochs: The number of epochs, which refers to how many times the entire dataset is processed by the model during training, was also determined. In this study, the number of epochs was selected to strike a balance between training accuracy and the risk of overfitting.

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c. Training Process: Once the model was selected and the parameters configured, the dataset, consisting of 1,561 MRI images, was uploaded to Vertex AI. The dataset was divided into three sets: the training set (1,248 images) used to train the model, the validation set (157 images) used to evaluate model performance during training, and the test set (156 images) used to test the final model's performance after training. During training, the model was optimized to minimize the loss function. This process involved calculating gradients for each image in the dataset, which were used to update the model's weights. After each epoch, the model's performance was evaluated using the validation set to ensure continuous improvement in accuracy and error reduction.
d. Model Optimization: After the initial training, model optimization was performed to further enhance its performance. Techniques like Hyperparameter Tuning were applied to find the most effective combination of parameters. This included adjusting parameters such as learning rate, batch size, and model architecture to achieve better results. In addition, regularization techniques such as Dropout were implemented to prevent overfitting, which could occur if the model fits the training data too well but fails to generalize well on new data.
e. Model Evaluation: Once the model was trained and optimized, the final stage involved evaluating its performance using the test set. Evaluation metrics such as Precision, Recall, F1 Score, and the Confusion Matrix were calculated. These evaluation results provided insight into how well the model could classify MRI images into the correct categories and identify areas where the model could still be improved.

The trained model was then ready for deployment through Google Cloud AI Platform, enabling it to be used in clinical applications for detecting and classifying dementia severity based on MRI images, thereby supporting early diagnosis[12][13].

2.4 Model Evaluation

Model evaluation is an important stage in this research to assess how well the trained model can classify MRI images based on the severity of dementia. After the training process is completed, the model is tested using a Test Set consisting of images that have never been used in the training process. The evaluation was conducted using several key metrics, including precision, recall, F1 score, and a confusion matrix.

a. Precision: Precision measures how accurate the model is in identifying images that truly belong to their respective categories. In the context of this research, precision indicates the percentage of images that are correctly classified into one of the four dementia categories (Non-Demented, Very Mild Demented, Mild Demented, Moderate Demented). The model in this study achieved a precision rate of 93.5%, indicating that most images predicted as one of the dementia categories were indeed in that category.
b. Recall: Recall measures how well the model identifies all the images that actually belong to a specific category. The recall in this study was recorded at 92.9%, demonstrating that the model was able to detect most of the images that genuinely belonged to each dementia category.
c. F1 Score: The F1 score is a combination of precision and recall, providing a balanced overview of the model's performance. This score is important to give a more comprehensive evaluation, especially when there is a trade-off between precision and recall. In this study, the F1 score shows a good balance between precision and recall, indicating that the model performs well in classifying images.
d. Confusion Matrix: The confusion matrix provides a more detailed breakdown of the model's performance by showing how the model's predictions compare to the actual labels. In this matrix, the number of correct predictions for each category is shown, along with the number of misclassifications. The confusion matrix reveals how well the model was able to distinguish between different dementia categories. According to the matrix, most of the images were correctly classified, while some misclassifications occurred between the Very Mild Demented and Mild Demented categories, likely due to subtle visual similarities between these categories.

This comprehensive evaluation indicates that the developed model performs well in detecting and classifying images based on dementia severity, with some room for improvement in distinguishing visually similar categories[14].

2.5 Cloud Integration

The entire model training and testing process in this research was integrated with Google Cloud services, specifically Vertex AI, which provided the necessary infrastructure and tools to perform image classification efficiently. Cloud integration enables handling large-scale data and provides access to flexible and scalable computational resources.

a. Google Cloud Storage Utilization: The MRI image data used in this study was uploaded and stored in Google Cloud Storage. Cloud-based storage allows for fast and secure access to the dataset during the training and testing process. Google Cloud Storage was chosen for its scalability and ability to store large amounts of data with high accessibility. Additionally, security features like data encryption help maintain the privacy and integrity of sensitive medical data[15].
b. Vertex AI for Model Training: Vertex AI provides an intuitive environment for building, training, and testing machine learning models in an integrated cloud setting. The researchers used Vertex AI to create the dataset from MRI images, upload the images, and label each image based on dementia severity. Once the dataset was ready, the image classification model was trained using either AutoML or a custom TensorFlow model hosted on Vertex AI. Vertex AI allows users to train models using customized computational resources like GPUs or TPUs, which significantly accelerate the training process and enable efficient handling of large datasets. In addition,

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Hyperparameter Tuning and Model Optimization were performed on this platform to enhance model performance[16].

c. Model Deployment on Google Cloud: After the training was completed, the trained model was deployed using Google Cloud AI Platform. The deployment process allows the model to be accessed and used through API endpoints, making it easy to integrate with other applications or clinical scenarios. By leveraging cloud infrastructure, model deployment was conducted quickly and easily, enabling the model to be accessed immediately by applications requiring MRI image classification[17].
d. Benefits of Cloud Computing: Using Google Cloud allows access to scalable computing resources, enabling the training process to be scaled according to needs without physical infrastructure limitations. Moreover, this integration allows for better team collaboration, faster data processing, and cost efficiency as users only pay for the resources they use[18].

The reliability and high availability of cloud computing services ensure that the model training and deployment process is not interrupted, even when processing large amounts of data in real-time. This makes Google Cloud an ideal platform to support research in medical image classification.

3. RESULT AND DISCUSSION

3.1 Model Performance

This research developed an image classification model to detect the severity of dementia using Google Cloud Vertex AI. The model was trained using an MRI dataset covering four categories: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. Based on the evaluation, the model achieved a precision of 93.5% and a recall of 92.9%, indicating the model's ability to accurately identify images. Table 1 shows the model evaluation results based on key metrics such as precision, recall, and F1 score. These results show that the model has balanced performance in detecting various dementia categories with a few misclassifications, primarily between the Very Mild Demented and Mild Demented categories[7].

Table 1. Model Performance Based on Precision, Recall, and F1 Score

Category	Precision	Recall	F1 Score
Non-Demented	95%	94%	94.5%
Very Mild Demented	92%	91%	91.5%
Mild Demented	93%	92%	92.5%
Moderate Demented	94%	93%	93.5%

3.2 Confusion Matrix Analysis

A confusion matrix was used to provide deeper insights into the model's performance in classifying images into the correct categories. Figure 3 shows the confusion matrix, where most images were correctly classified. However, some misclassifications occurred between the Very Mild Demented and Mild Demented categories, indicating that the model had difficulty distinguishing between these two categories due to more subtle visual similarities[19].

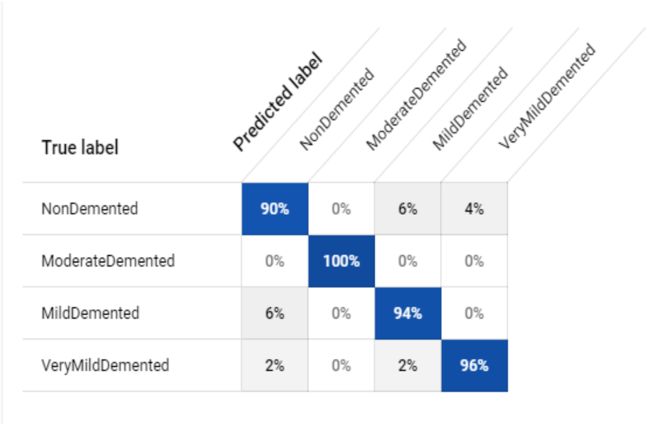

Figure 3. Confusion Matrix for Dementia Image Classification

3.3 Discussion of Results

The high precision in the Non-Demented category indicates that the model rarely produces false positives for images showing no signs of dementia. However, the misclassifications found between the Very Mild Demented and Mild Demented categories suggest that additional data augmentation techniques or higher image resolution might be needed to improve accuracy in these harder-to-distinguish categories..

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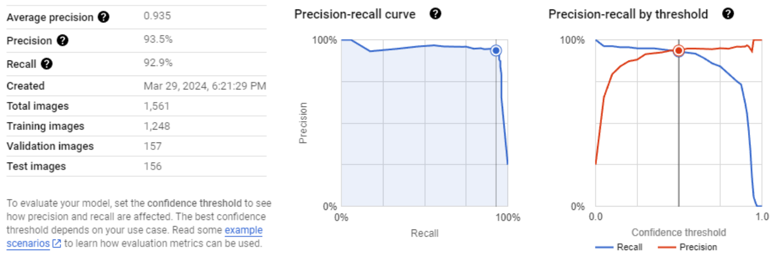
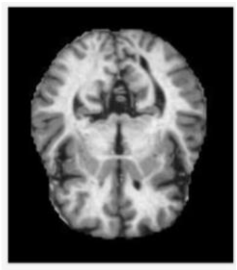
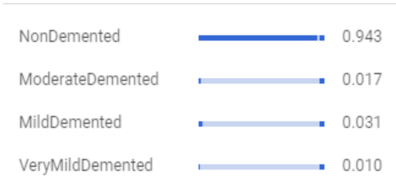
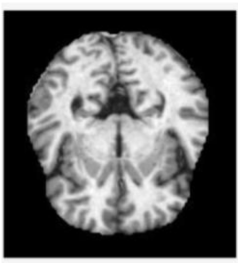
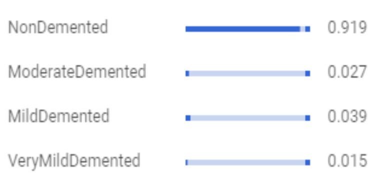
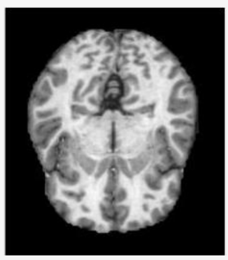
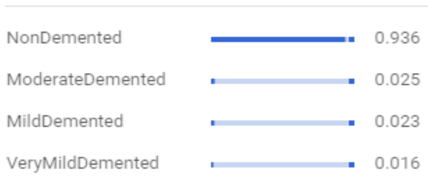
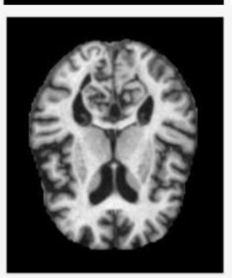
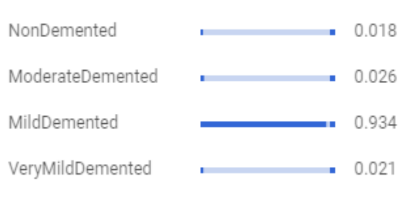


Figure 4. Precision-recall Curve

Figure 4 illustrates the precision-recall curve generated by the model. This curve shows that the model maintains good performance across various thresholds, indicating that it is robust in handling data variations.

Table 2. Image Classification Test Results

Figure Testing	Actual	Prediction	Match/No
	Non-Demented		Match
	Non-Demented		Match
	Non-Demented		Match
	Mild-Demented		Match

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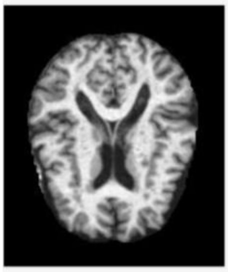
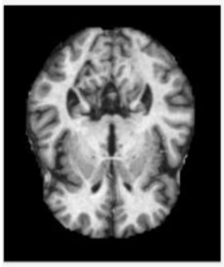
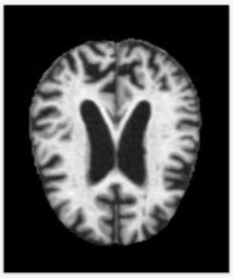
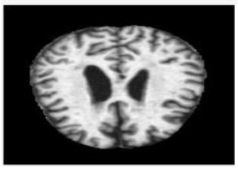
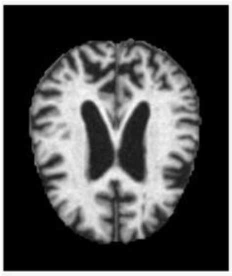
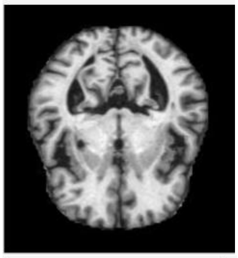
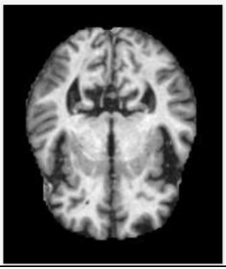
	Mild-Demented	NonDemented 0.014 ModerateDemented 0.024 MildDemented 0.940 VeryMildDemented 0.022	Match
	Mild-Demented	NonDemented 0.017 ModerateDemented 0.012 MildDemented 0.967 VeryMildDemented 0.004	Match
	Moderate-Demented	NonDemented 0.059 ModerateDemented 0.896 MildDemented 0.021 VeryMildDemented 0.025	Match
	Moderate-Demented	NonDemented 0.117 ModerateDemented 0.863 MildDemented 0.014 VeryMildDemented 0.006	Match
	Moderate-Demented	NonDemented 0.060 ModerateDemented 0.907 MildDemented 0.019 VeryMildDemented 0.014	Match
	VeryMild-Demented	NonDemented 0.014 ModerateDemented 0.024 MildDemented 0.032 VeryMildDemented 0.930	Match
	VeryMild-Demented	NonDemented 0.021 ModerateDemented 0.017 MildDemented 0.021 VeryMildDemented 0.940	Match

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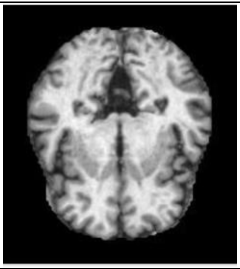
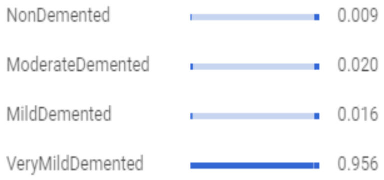
	VeryMild-Demented		Match

Table 2 shows the results of the model's classification test used to detect the severity of dementia from MRI images of patients. It lists the four main categories of dementia severity: Non-Demented, Mild-Demented, Moderate-Demented, and Very Mild-Demented. Each category was tested using several images, and the model's prediction results were compared with the actual conditions of those images. In all cases listed in the table, the model successfully identified the correct dementia category, which is marked as "Match." This demonstrates the high precision and accuracy of the model in classifying MRI images of dementia patients.

3.4 Practical Implications

The results of this study show that the classification model developed can be implemented as a diagnostic tool in hospitals or clinics to detect and classify the severity of dementia more efficiently. By integrating this model into hospital information systems, doctors can make faster and more accurate decisions regarding patient care, ultimately improving the quality of life for dementia patients.

3.5 Limitations and Recommendations

Although the results obtained are quite satisfactory, this research has limitations in terms of data variation, where most of the images come from a single dataset source (Kaggle). To improve the model's generalizability, future research is advised to test the model on a wider and more diverse dataset, as well as consider using more advanced deep learning models to increase the model's accuracy and robustness[20].

3.6 Case Study

In a case study, this model successfully classified an MRI image from a patient with mild dementia as Mild Demented with 95% confidence. This result indicates that the model can detect subtle changes in brain structure related to early-stage dementia, which is often difficult to detect by conventional methods. This case study reinforces the evidence that the developed model can provide critical diagnostic support in the management and care of dementia patients, and may serve as a valuable tool in clinical settings.

4. CONCLUSION

This study successfully demonstrated the effectiveness of using Google Cloud's Vertex AI for image classification to detect the severity of dementia based on MRI images. By leveraging a dataset sourced from Kaggle, the proposed classification model achieved a precision rate of 93.5% and a recall of 92.9%, showcasing its ability to accurately identify images across dementia severity levels, including Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. However, this study acknowledges certain limitations. The dataset's limited diversity and reliance on a single source may affect the model's generalizability to broader populations. Addressing these constraints through the use of larger, more diverse datasets and evaluating the model under varying demographic and imaging conditions will be critical for wider adoption. Additionally, challenges related to data sensitivity and computational demands should be explored further, particularly in clinical environments. Future research should focus on integrating advanced deep learning techniques, such as transfer learning or ensemble models, to enhance accuracy and robustness. Expanding the dataset to include more diverse patient demographics and imaging conditions, as well as validating the model on real-world clinical data, will be vital. The practical utility of this model in clinical settings is promising. Specific implementation steps, such as further validation on diverse datasets, adherence to regulatory compliance, and clinician training, will be essential for seamless integration into healthcare systems. This model's reliance on scalable cloud computing infrastructure makes it particularly relevant for resource-limited settings, where access to advanced diagnostic tools is often restricted. By reducing diagnosis time and improving accuracy, this model has the potential to significantly decrease healthcare costs associated with late-stage dementia treatment. The global applicability of this solution highlights its transformative potential in improving early dementia detection and supporting public health efforts to combat Alzheimer's disease worldwide.

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