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Research Article

Enhancing Alzheimer's Disease Diagnosis with K-NN: A Study on Pre-processed MRI Data

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Abstract:
Alzheimer's disease (AD) is a progressive neurodegenerative disorder characterized by cognitive decline and memory loss, necessitating early and accurate diagnosis for effective intervention. This study evaluates the performance of the K-Nearest Neighbor (K-NN) algorithm on a pre-processed Alzheimer MRI dataset, focusing on the challenge of imbalanced classes. The dataset, sourced from Kaggle, comprises 6400 MRI images resized to 128x128 pixels and categorized into four classes: Non-Demented, Mild Demented, Moderate Demented, and Very Mild Demented. Pre-processing involved segmentation using the Canny edge detection method and feature extraction through Hu Moments. The dataset was split into training (80%) and testing (20%) sets, with features scaled to a mean of 0 and variance of 1. The K-NN algorithm was evaluated using cross-validation with five different k values, revealing moderate performance metrics: accuracy ranging from 45.86% to 50.47%, precision from 41.87% to 47.00%, recall from 45.86% to 50.47%, F1-score from 42.42% to 47.58%, and ROC AUC from 55.18% to 58.87%. The results highlight the significant impact of class imbalance on the algorithm's performance, particularly for the underrepresented Moderate Demented class. This study underscores the need for techniques to address class imbalance to enhance classification accuracy. Future research should explore advanced methods such as data augmentation, re-sampling, and ensemble learning, as well as the evaluation of other machine learning models. These findings contribute to the field of medical image analysis and have practical implications for improving diagnostic tools for Alzheimer's disease.

Keywords: Alzheimer's Disease, K-Nearest Neighbor, MRI, Class Imbalance, Hu Moments.

Dataset link: https://www.kaggle.com/datasets/sachinkumar413/alzheimer-mri-dataset

1. Introduction

Alzheimer's disease (AD) is one of the most prevalent neurodegenerative disorders, significantly impacting the aging population worldwide. This progressive condition leads to severe cognitive decline, affecting memory, thinking, and behaviour. Early and accurate diagnosis of Alzheimer's disease is crucial for effective treatment and intervention. Magnetic Resonance Imaging (MRI) has emerged as a valuable non-invasive tool for diagnosing Alzheimer's disease. MRI provides detailed images of the brain, allowing for the detection of structural abnormalities associated with various stages of dementia. In recent years, the availability of large-scale medical imaging datasets, such as those found on Kaggle, has opened new avenues for applying machine learning techniques to enhance diagnostic accuracy [1], [2].

The primary problem addressed in this research is the classification of Alzheimer's disease stages using MRI images, specifically focusing on the challenge of imbalanced datasets. Imbalanced datasets are common in medical imaging, where certain conditions or stages of a disease are underrepresented. This imbalance can lead to biased machine learning models that perform well on majority classes but poorly on minority classes. Accurate classification of all stages of Alzheimer's, particularly the less common moderate and very mild stages, is essential for timely intervention and treatment planning. Therefore, it is imperative to develop and evaluate methods that can handle class imbalance and still provide reliable classification performance. This research aims to evaluate the effectiveness of the K-Nearest Neighbor (K-NN) algorithm [3], [4] in classifying Alzheimer's disease stages using a pre-processed MRI dataset. The dataset, sourced from Kaggle, includes 6400 MRI images divided into four classes: Non-Demented, Mild Demented, Moderate Demented, and Very Mild Demented. The images have been pre-processed by resizing to 128x128 pixels, segmenting using the Canny edge detection method, and extracting features using Hu Moments. The primary objective is to assess the performance of K-NN in terms of accuracy, precision, recall, and F1-score across these imbalanced classes [5]–[7].

The research questions guiding this study are: How accurately can the K-NN algorithm classify the different stages of Alzheimer's disease using the given MRI dataset? What impact does the class imbalance have on the classification performance? How do pre-processing techniques like image resizing, segmentation, and feature extraction influence the results? These questions aim to uncover the strengths and limitations of K-NN in this specific application and to identify potential areas for improvement in handling imbalanced medical datasets. The scope of this research is confined to the evaluation of the K-NN algorithm on a specific pre-processed MRI dataset of Alzheimer's disease. While K-NN is known for its simplicity and effectiveness in various classification tasks, this study will specifically focus on its application in the context of medical imaging and class imbalance. Limitations of this research include the reliance on a single dataset and specific pre-processing techniques, which may not generalize to other datasets or conditions. Additionally, the study does not explore other machine learning algorithms or advanced techniques for handling class imbalance, which could be areas for future research.

The contributions of this research are manifold. Firstly, it provides a comprehensive evaluation of K-NN on a challenging and clinically relevant task of classifying Alzheimer's disease stages. Secondly, it highlights the impact of class imbalance on classification performance, offering insights into the necessity for methods to address this issue. Lastly, the research underscores the importance of pre-processing steps, such as image resizing, segmentation, and feature extraction, in enhancing the performance of machine learning models in medical imaging. These contributions aim to advance the field of medical image analysis and support the development of more accurate diagnostic tools for Alzheimer's disease.

2. Method

This research follows a quantitative design aimed at evaluating the performance of the K-Nearest Neighbor (K-NN) algorithm on an imbalanced MRI dataset for Alzheimer's disease classification. The study involves several stages: data pre-processing, feature extraction, dataset splitting, normalization, model training, and performance evaluation. Each stage is designed to systematically handle the complexities of medical image analysis and address the challenges posed by class imbalance in the dataset [8]–[10]. **Figure 1** illustrates a visual overview of the entire research procedure.

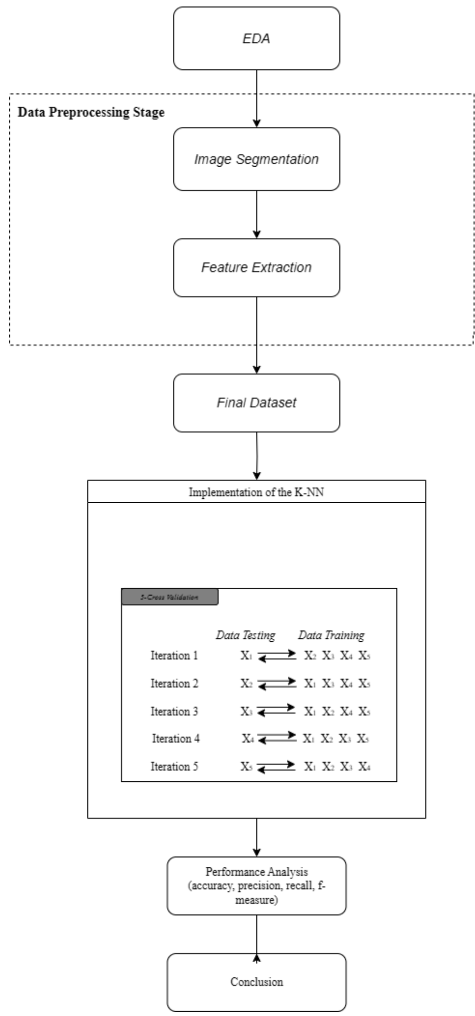

Figure 1: Evaluation Process for a K-NN

Sample or Data Selection:

The dataset used in this study consists of 6400 pre-processed MRI images, sourced from Kaggle. The images are categorized into four classes: Non-Demented (3200 images), Mild Demented (896 images), Moderate Demented (64 images), and Very Mild Demented (2240 images). This distribution highlights the imbalance, with some classes being significantly underrepresented. Each image is resized to 128×128 pixels, ensuring uniformity for further processing. To visualize the data, we will present several plots, including segmentation results, scatter plots for all combinations of Hu Moments, and various statistical visualizations, which help in understanding the distribution and relationships of the features within the dataset.

Data Collection Process

The dataset was collected from multiple sources, including hospitals, public repositories, and websites, ensuring a diverse set of MRI images. Each image was pre-processed to standardize the size (128×128 pixels) and segmented using the Canny edge detection method. This segmentation helps in highlighting the edges and important structures within the MRI images, which are crucial for accurate feature extraction. Visualizations such as segmentation results provide insight into the effectiveness of the Canny method in isolating relevant structures within the images.

Data Analysis Methods

The data analysis involves several steps:

a. Segmentation Using Canny Method:

The Canny edge detection algorithm was applied to each MRI image. The Canny method works by detecting edges in an image using a multi-stage process that involves noise reduction, gradient calculation, non-maximum suppression, and edge tracking by hysteresis [11]–[13].

$$Canny(I) = \{edge_{ij} \mid I \text{ is the input image}\} \quad (1)$$

Example visualization: The segmentation results will show the detected edges, demonstrating the effectiveness of this method in highlighting important brain structures.

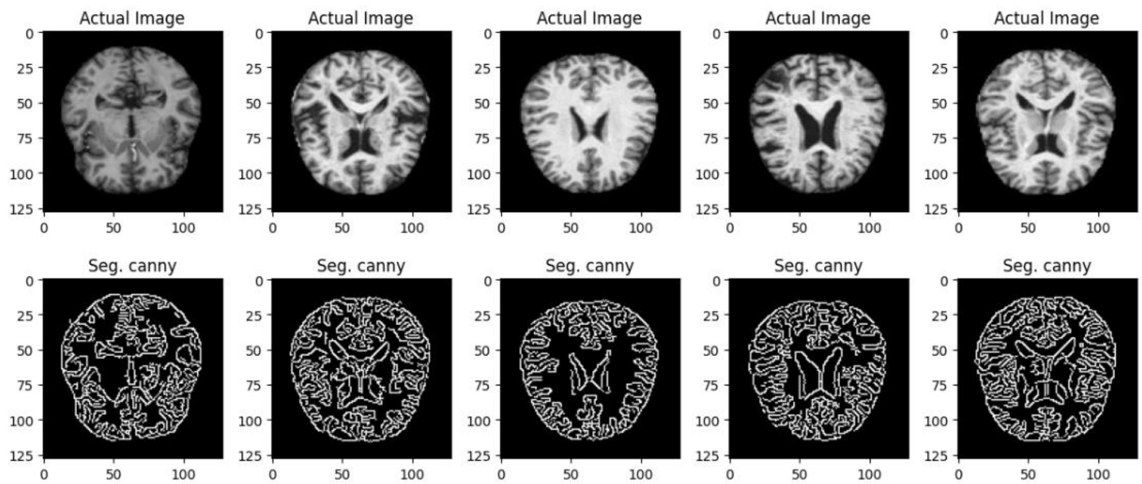

Figure 2: Normal Class

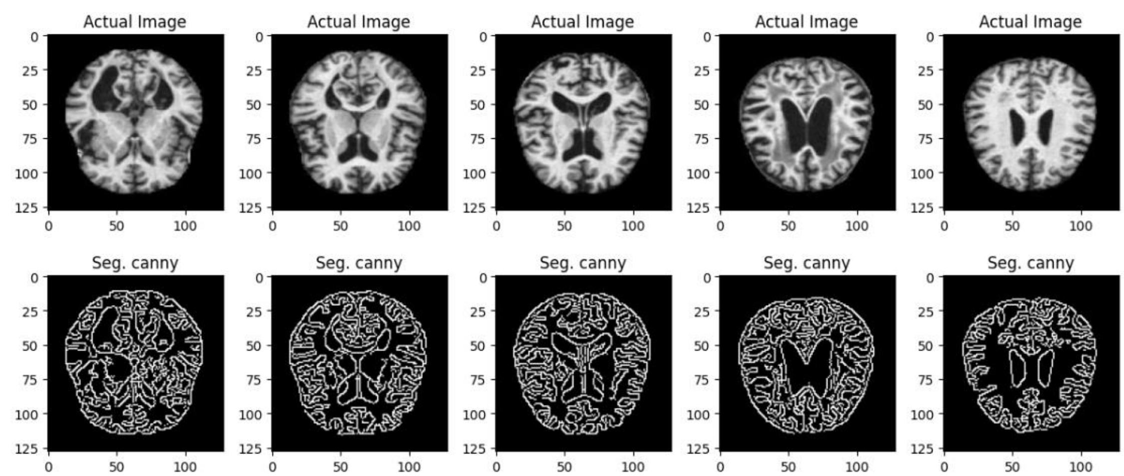

Figure 3: Mild Demented Class

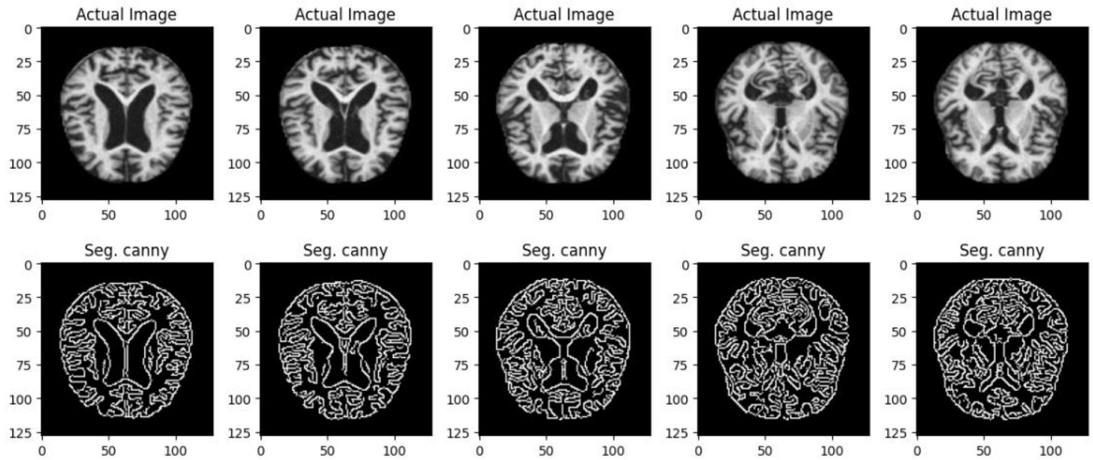

Figure 4: Moderate Demented Class

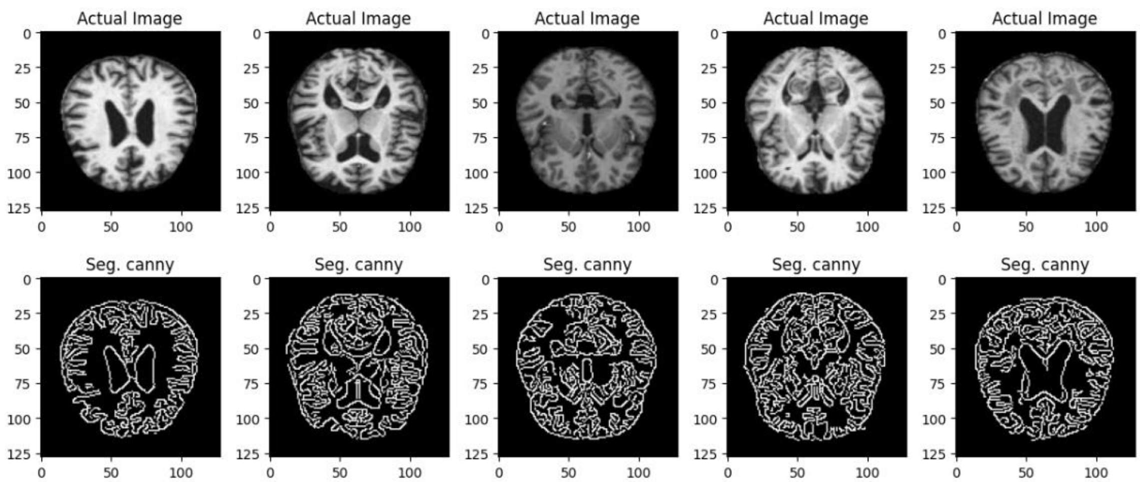

Figure 5: Very Mild Demented Class

b. Feature Extraction Using Hu Moments:

Hu Moments are seven invariant moments used to describe the shape of an object in an image [14]–[16]. These moments are invariant to image transformations such as translation, scale, and rotation.

$$H = \sum_{x,y} (x - \bar{x})^n (y - \bar{y})^m I(x, y) \quad (1)$$

Example visualization: Scatter plots for all combinations of Hu Moments will be displayed to show the distribution and relationships between these features.

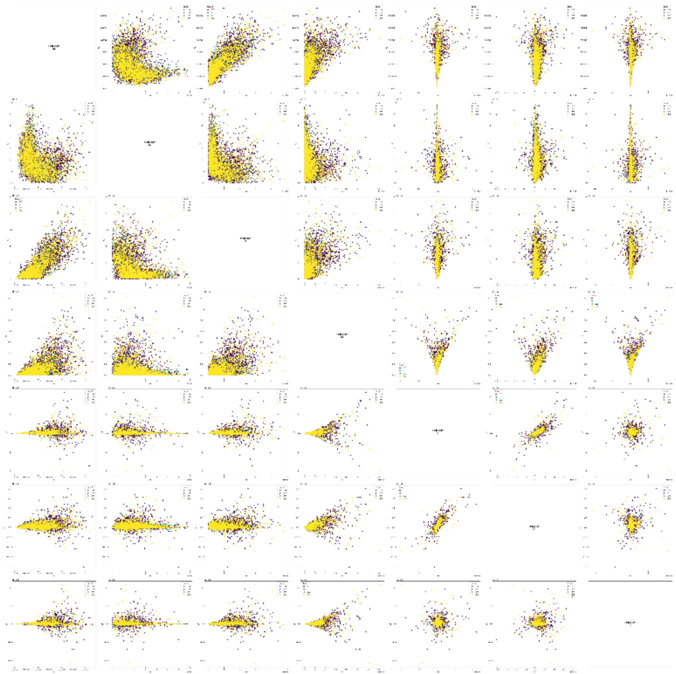

Figure 6: Scatter Plots for All Combinations of Hu Moments

c. Dataset Splitting and Normalization:

The dataset was split into training (80%) and testing (20%) sets [8], [17]. Each feature was then scaled to have a mean of 0 and variance of 1 to ensure that the K-NN algorithm performs optimally.

$$Scale\ Value = \frac{X - \mu}{\sigma} \tag{1}$$

Example visualization: Boxplots of the Hu Moments will illustrate the distribution of features after scaling.

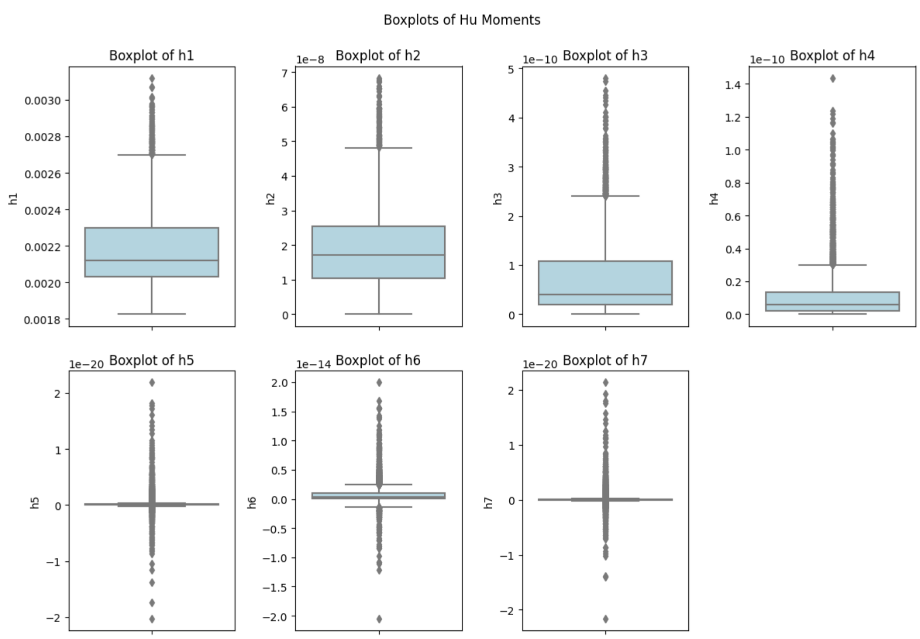

Figure 7: Boxplots of Hu Moments

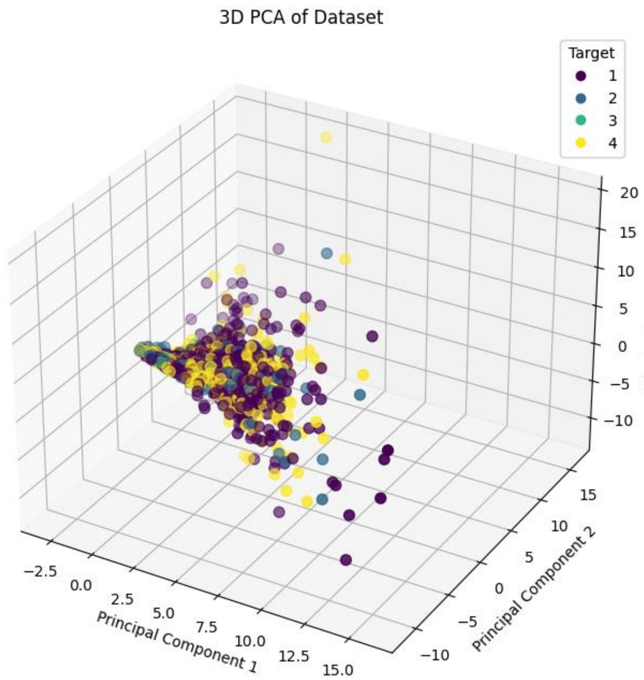

Figure 8: 3D PCA of Dataset

d. K-Nearest Neighbor (K-NN) Implementation:

The K-NN algorithm was used for classification. For each test sample, the algorithm identifies the k-nearest training samples and assigns the most common class among them [18]–[20]. The distance metric used is Euclidean distance.

$$d(p,q) = \sqrt{\sum_{i=1}^{n}(p_i - q_i)^2} \tag{1}$$

Performance metrics such as accuracy, precision, recall, and F1-score were calculated to evaluate the model. The formulas for these metrics are [21]–[24]:

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}}$$

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \tag{3}$$

$$F1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

3. Result and Discussion

The K-Nearest Neighbor (K-NN) algorithm was evaluated using cross-validation with five different values of k. The performance metrics for each value of k are summarized in the **Table 1**.

Table 2: Performance Metrics Across 5-Fold Cross-Validation for the K-NN Algorithm

K-n	Metrics			
	Accuracy	***Precision***	***Recall***	***F-Measure***
K-1	47.27%	44.39%	47.27%	44.76%
K-2	45.86%	41.87%	45.86%	42.42%
K-3	49.77%	46.17%	49.77%	46.77%
K-4	50.47%	47%	50.47%	47.58%
K-5	48.28%	44.36%	48.28%	44.53%
$\sum Avg$	48.33%	44.76%	48.33%	45.21%

To provide a clearer understanding of these results, several visualizations were generated, including performance graphs and confusion matrices. These visualizations help in analysing the performance of the K-NN algorithm across different values of k and understanding the distribution of predictions among the different classes. The dataset was pre-processed by resizing the MRI images to 128×128 pixels, followed by segmentation using the Canny edge detection method. Feature extraction was performed using Hu Moments, and the dataset was split into training (80%) and testing (20%) sets. The features were scaled to ensure a mean of 0 and a variance of 1.

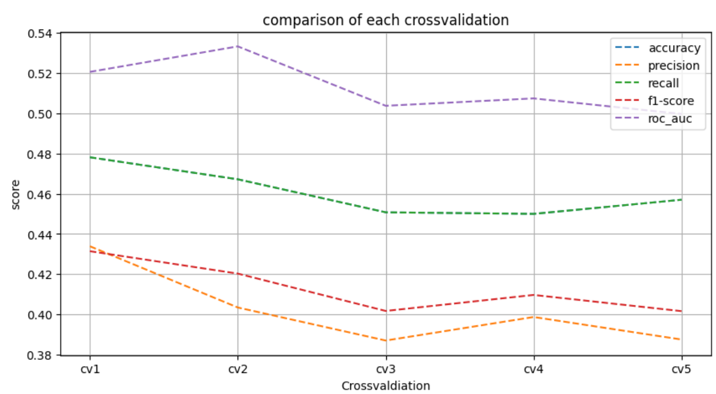

Figure 9: Performance Comparison of Each Cross-validation Fold

Performance metrics were visualized through graphs to compare the accuracy, precision, recall, F1-score, and ROC AUC across different values of k. Additionally, confusion matrices were plotted to illustrate the classification performance for each class. The results indicate that the K-NN algorithm achieved the highest accuracy of 50.47% with k=4. Precision and recall were consistent across different values of k, reflecting the impact of class imbalance on the model's performance. The F1-score and ROC AUC values also suggest moderate performance, with the highest F1-score (47.58%) and ROC AUC (58.87%) observed for k=4 and k=1, respectively. The study found that the K-NN algorithm's performance is significantly affected by the class imbalance in the dataset. While the algorithm shows moderate accuracy, precision, and recall, the performance metrics highlight the challenges in classifying the less represented classes, such as Moderate Demented.

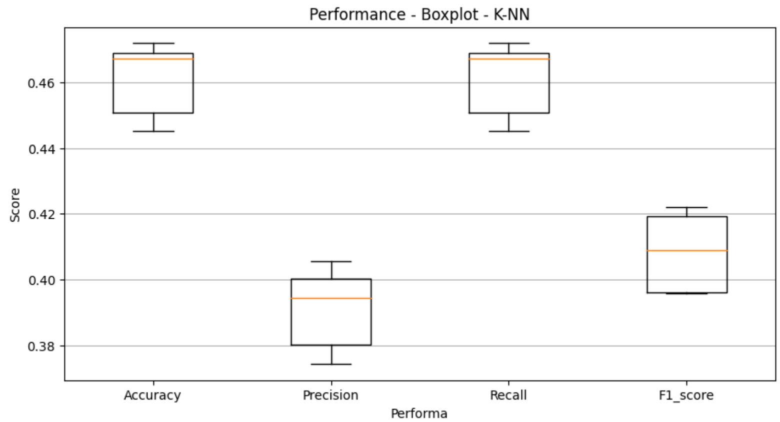

Figure 10: Performance Boxplot of the K-NN

Discussion

The evaluation of the K-NN algorithm on the imbalanced Alzheimer's MRI dataset revealed that the algorithm performs moderately well, with accuracy ranging from 45.86% to 50.47%. The class imbalance significantly impacted the precision and recall, particularly for the underrepresented classes. These findings emphasize the need for handling class imbalance more effectively to improve classification performance. The results align with existing research that highlights the challenges of using K-NN for imbalanced datasets. Previous studies have shown that K-NN can struggle with minority classes, leading to lower precision and recall for these classes. This research confirms these findings and suggests that additional techniques, such as data augmentation or re-sampling, may be necessary to address these issues.

The practical implications of this research are significant for the early diagnosis of Alzheimer's disease. Despite the moderate performance, the K-NN algorithm can still provide valuable insights into the classification of Alzheimer's stages. However, the results suggest that improving the handling of class imbalance could lead to more reliable diagnostic tools, potentially aiding in more accurate and timely interventions. The primary limitation of this research is the reliance on a single dataset and specific pre-processing techniques. The class imbalance in the dataset posed significant challenges for the K-NN algorithm, affecting its overall performance. Additionally, the study did not explore other machine learning algorithms or advanced techniques for handling class imbalance, which could provide better results.

Future research should focus on exploring techniques to mitigate class imbalance, such as data augmentation, re-sampling, or using more sophisticated algorithms like ensemble methods. Additionally, evaluating the performance of other machine learning models on this dataset could provide a more comprehensive understanding of the best approaches for Alzheimer's disease classification. Expanding the dataset and incorporating additional features could also enhance the model's accuracy and reliability. To further illustrate the findings, performance graphs and confusion matrices for each value of k are provided. These visualizations offer a detailed view of the classification results, highlighting the strengths and weaknesses of the K-NN algorithm in this context.

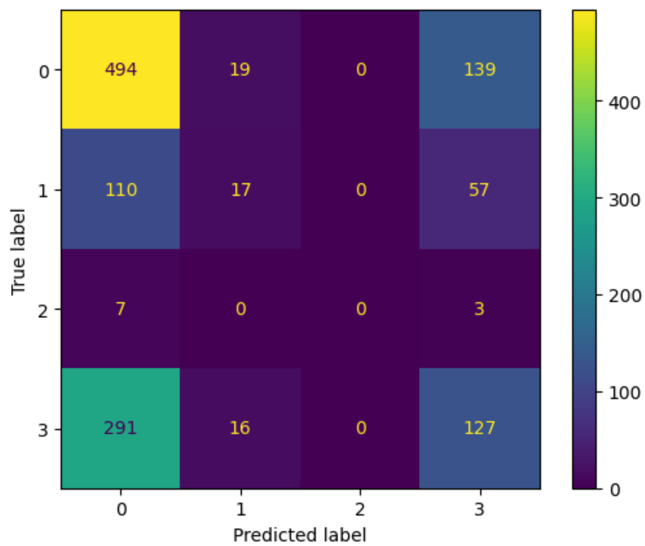

Figure 11: Confusion Matrix of the K-NN

4. Conclusion

In summary, this study evaluated the performance of the K-Nearest Neighbor (K-NN) algorithm on an imbalanced Alzheimer MRI dataset using pre-processing techniques such as image resizing, Canny segmentation, and Hu Moments for feature extraction. The K-NN algorithm demonstrated moderate performance, with the highest accuracy of 50.47% and corresponding precision, recall, F1-score, and ROC AUC metrics indicating the challenges posed by class imbalance. The research questions were addressed, revealing that K-NN can classify Alzheimer's disease stages to a certain extent but struggles with minority classes due to the imbalance. The findings underscore the importance of addressing class imbalance and suggest that further improvement in classification performance can be achieved through advanced techniques.

The contributions of this research lie in providing a detailed evaluation of K-NN for Alzheimer's MRI image classification, highlighting the impact of class imbalance, and offering insights into pre-processing methods. These results add to the growing body of knowledge on machine learning applications in medical imaging. For future research, it is recommended to explore methods to mitigate class imbalance, such as data augmentation, re-sampling, or ensemble approaches, and to investigate other machine learning models to improve classification accuracy and reliability. Expanding the dataset and incorporating additional features could also enhance the model's effectiveness in early diagnosis of Alzheimer's disease, ultimately aiding in better clinical decision-making.

References:

[1] N. Rismayanti, A. Naswin, U. Zaky, M. Zakariyah, and D. A. Purnamasari, “Evaluating Thresholding-Based Segmentation and Humoment Feature Extraction in Acute Lymphoblastic Leukemia Classification using Gaussian Naive Bayes,” *Int. J. Artif. Intell. Med. Issues*, vol. 1, no. 2, 2023.

[2] A. Maulidinnawati, “Classification Optimization of Skin Cancer Using the Adaboost Algorithm,” *… J. Artif. Intell. Med. …*, 2023.

[3] N. D. Mu'azu, "K-nearest neighbor based computational intelligence and RSM predictive models for extraction of Cadmium from contaminated soil," *Ain Shams Eng. J.*, vol. 14, no. 4, 2023, doi: 10.1016/j.asej.2022.101944.

[4] R. Siddalingappa, "K-nearest-neighbor algorithm to predict the survival time and classification of various stages of oral cancer: a machine learning approach," *F1000Research*, vol. 11, p. 70, 2022, doi: 10.12688/f1000research.75469.2.

[5] M. Novitasari, "Classification of House Buildings Based on Land Size Using the K-Nearest Neighbor Algorithm," *AIP Conference Proceedings*, vol. 2499. 2022, doi: 10.1063/5.0104960.

[6] E. Alcaras, "Machine Learning Approaches for Coastline Extraction from Sentinel-2 Images: K-Means and K-Nearest Neighbour Algorithms in Comparison," *Communications in Computer and Information Science*, vol. 1651. pp. 368–379, 2022, doi: 10.1007/978-3-031-17439-1_27.

[7] C. Feng, "An Enhanced Quantum K-Nearest Neighbor Classification Algorithm Based on Polar Distance," *Entropy*, vol. 25, no. 1, 2023, doi: 10.3390/e25010127.

[8] R. Setiawan and H. Oumarou, "Classification of Rice Grain Varieties Using Ensemble Learning and Image Analysis Techniques," *Indones. J. Data …*, 2024.

[9] A. Aisyah and S. Anraeni, "Analisis penerapan metode K-Nearest Neighbor (K-NN) pada dataset citra penyakit malaria," *Indones. J. Data Sci.*, 2022.

[10] I. P. Putri, "Analisis Performa Metode K- Nearest Neighbor (KNN) dan Crossvalidation pada Data Penyakit Cardiovascular," *Indones. J. Data Sci.*, vol. 2, no. 1, pp. 21–28, 2021, doi: 10.33096/ijodas.v2i1.25.

[11] M. R. Sharan, "Classification of Medicinal Leaf by Using Canny Edge Detection and SVM Classifier," *2022 Int. Conf. Futur. Technol. INCOFT 2022*, 2022, doi: 10.1109/INCOFT55651.2022.10094461.

[12] S. K. T. Hwa, "Tuberculosis detection using deep learning and contrast-enhanced canny edge detected X-Ray images," *IAES Int. J. Artif. Intell.*, vol. 9, no. 4, pp. 713–720, 2020, doi: 10.11591/ijai.v9.i4.pp713-720.

[13] Z. Hu, "Canny Algorithm Enabling Precise Offline Line Edge Roughness Acquisition in High-Resolution Lithography," *ACS Omega*, 2022, doi: 10.1021/acsomega.2c06769.

[14] Y. Jusman, "Classification System of Malaria Disease with Hu Moment Invariant and Support Vector Machines," *Proc. - 2022 2nd Int. Conf. Electron. Electr. Eng. Intell. Syst. ICE3IS 2022*, pp. 365–368, 2022, doi: 10.1109/ICE3IS56585.2022.10010304.

[15] Y. Jusman, "Classification System for Leukemia Cell Images based on Hu Moment Invariants and Support Vector Machines," *Proc. - 2021 11th IEEE Int. Conf. Control Syst. Comput. Eng. ICCSCE 2021*, pp. 137–141, 2021, doi: 10.1109/ICCSCE52189.2021.9530974.

[16] B. P. Sari, "Classification System for Cervical Cell Images based on Hu Moment Invariants Methods and Support Vector Machine," *2021 Int. Conf. Intell. Technol. CONIT 2021*, 2021, doi: 10.1109/CONIT51480.2021.9498353.

[17] N. Rismayanti and A. P. Utami, "Improving Multi-Class Classification on 5-Celebrity-Faces Dataset using Ensemble Classification Methods," *Indones. J. Data …*, 2023.

[18] Q. Zhang, "Enhanced Harris hawks optimization-based fuzzy k-nearest neighbor algorithm for diagnosis of

Alzheimer's disease," *Comput. Biol. Med.*, vol. 165, 2023, doi: 10.1016/j.compbiomed.2023.107392.

[19] D. C. E. Saputra, "K-Nearest Neighbor of Beta Signal Brainwave to Accelerate Detection of Concentration on Student Learning Outcomes," *Eng. Lett.*, vol. 30, no. 1, pp. 318–324, 2022.

[20] D. Lu, "Effective detection of Alzheimer's disease by optimizing fuzzy K-nearest neighbors based on salp swarm algorithm," *Comput. Biol. Med.*, vol. 159, 2023, doi: 10.1016/j.compbiomed.2023.106930.

[21] H. Azis, L. Syafie, F. Fattah, and ..., "Unveiling Algorithm Classification Excellence: Exploring Calendula and Coreopsis Flower Datasets with Varied Segmentation Techniques," *2024 18th Int. …*, 2024.

[22] M. M. Baharuddin, T. Hasanuddin, and H. Azis, "Analisis Performa Metode K-Nearest Neighbor untuk Identifikasi Jenis Kaca," *Ilk. J. Ilm.*, vol. 11, no. 28, pp. 269–274, 2019.

[23] H. Azis, F. Fattah, and P. Putri, "Performa Klasifikasi K-NN dan Cross-validation pada Data Pasien Pengidap Penyakit Jantung," *Ilk. J. Ilm.*, vol. 12, no. 2, pp. 81–86, 2020.

[24] H. Azis, F. T. Admojo, and E. Susanti, "Analisis Perbandingan Performa Metode Klasifikasi pada Dataset Multiclass Citra Busur Panah," *Techno.Com*, vol. 19, no. 3, 2020.