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Evaluating the Impact of Image Compression Rates on Machine Learning Models Accuracy in Classification Tasks

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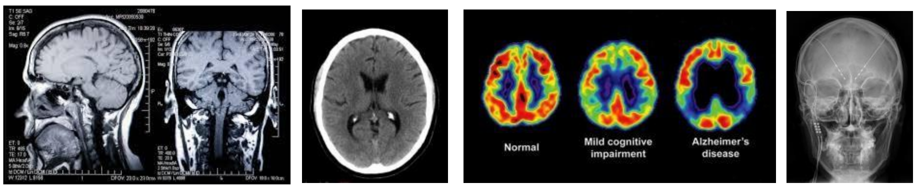
***Abstract*— Model selection in machine learning remains a critical challenge, particularly in medical image processing, where achieving high accuracy while managing computational constraints is essential. The growing use of artificial intelligence (AI) techniques in various applications, such as telemedicine, digital pathology, and healthcare, has highlighted the importance of balancing model performance with efficient data handling. Image compression, especially in resource-constrained environments, plays a significant role in maintaining this balance, ensuring fast transmission and storage without compromising diagnostic reliability. This research focuses on the impact of image compression rates on machine-learning model accuracy in medical images. The study applies experiments on nearly 7,000 Alzheimer's disease images across four phases, evaluating five machine-learning models under varying compression ratios and image sizes, revealing significant performance differences. Logistic regression consistently demonstrated the best performance, even with deteriorated image quality due to compression. The findings offer insights into optimizing compression levels for reliable classification and guide the selection of models resilient to compression artifacts, crucial for applications in telemedicine and AI-driven diagnostics.**

***Keywords*— Machine-Learning, Alzheimer Disease, Dementia, Medical images, Image Compression Ratio**

I. INTRODUCTION

The classification of images and predictive is a major area of study and a key focus for researchers, especially in the medical field. There are many types of images, such as Magnetic Reasoning Images (MRI), Computed tomography (CT), X-ray, Positron Emission Tomography (PET), etc. Fig 1 shows different images of the human brain [1]. These images are used to diagnose different types of diseases, as well as where they are found (in the kidneys, liver, uterus, heart, etc.), the stage at which it is in, and the region of interest within the organ itself (ROI) [2]. Machine-learning models for classification may be satisfied and built using a variety of image kinds and formats based on datasets (DS) that can be obtained from a wide range of sources and used for medical diagnosis. Nevertheless, these photos are frequently presented as compression images to reduce the image size, and then enable to increase in the volume of the image data set for model accuracy [3]. Machine learning models are algorithms designed to recognize patterns in data and make predictions or decisions without being explicitly programmed. They can be broadly categorized into three types: Supervised Learning, Un- supervised Learning and forecasting models [4]. In this study, five supervised learning models are used, which are: Support Vector Machine (SVM) [5], Logistic Regression (LG) [6], Decision Tree (DT), K-Nearest Neighbor (KNN) [7], and Artificial Neural Network (ANN) [8].



MRI CT PET X-Ray

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Fig.1. Different types of Medical Images of Human Brain

The medical images are concerned with Alzheimer's disease(AD) so, the study will focus on the brain area that shows the illness remarks in different stages. The decrease in the size of the hippocampus in the brain is one of the important signs that appear in medical images, and doctors can diagnose the disease through it [1]. a Depression, social disengagement, and memory loss are important clinical indicators. The early identification is important because it implies that the pathogenesis of AD starts long before symptoms such as obvious memory loss appear[2]. Fig 2 shows the Hippocampus area (the first mark of AD).

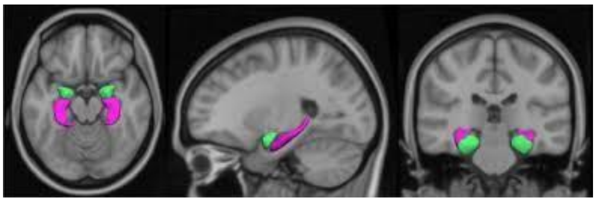

Fig.2. MRI Image (Hippocampus region) of Human Brain

There are three different data sets used in this research, the first is original dataset about the brain of Alzheimer disease with four stages are Non-Demented, Mild Demented, Very Mild Demented, and Moderate Demented based on Kaggle platform named Alzheimer's Disease(4 classes of images). Are JPEG sized in (176*208) of 5789 different image of brain. The regain of interest ROI is the Hippocampus size. The second and the third datasets are compressed images. As it clearly in experiment section. The paper is structured as follows: Section II presents the problem statement, highlighting key challenges and objectives. Section III introduces the dataset used in this experiment. Section IV reviews literature review to summarizing prior studies and methodologies. Section V demonstrates the study's contribution. The details of the proposed methodology are illustrated in section VI, while section VII discusses experimental results and the comparisons show in VIII. In IX, challenges will be discussed, and in X, the conclusion and future work section is at last presented.

II. PROBLEM STATEMENT

Diagnostic and decision-making in medicine rely heavily on medical imagery, where the image compression rate affects image quality. With the rapid advancement of medical imaging technologies, the need for compression techniques has grown to improve storage and processing efficiency. However, compression can deteriorate image quality, potentially compromising the accuracy of machine learning models in critical tasks. The appropriate compression ratio for optimal model performance is unknown, and balancing data handling with diagnostic reliability remains a challenge.

III. DATASETS

There are three different data sets: the first is original dataset about the brain of Alzheimer disease with four stages are Non-Demented, Mild Demented, Very Mild Demented, and Moderate Demented based on Kaggle platform named Alzheimer's Disease(4 classes of images). Are JPEG sized in (176*208) of 5789 different image of brain. The regain of interest ROI is the Hippocampus size. The second and the third datasets are compressed images. As it is clearly in experiment section

IV. LITERATURE REVIEW

Jo and etil [3]: This study examines the effect of image compression on deep learning models for classifying mammograms as malignant or non-malignant. CNN models performed best with compression ratios of 5 K (AUROC: 0.87, AUPRC: 0.75), while higher compression significantly reduced performance. Saliency maps showed better alignment with radiologist labels for less compressed images. The experiment also analyzed the impact of compression using measures like PSNR, but specific model performance metrics were not provided.

Poyser, and etil [4]: Examined the relationship between deep neural network performance and the level of lossy compression applied. The results inform that performance decreases significantly below a JPEG quality (quantization) level in the CNN model on images and video. It also offers insights into loss compression resilience

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and retraining strategies although, did not focus on traditional ML-models or pathology images.

Yijiang ,and etil [5]: The research evaluated the impact of image compression using JPEG and JPEG2000 formats on breast cancer image segmentation with a deep learning network. The study specifically focused on segmentation tasks rather than classification and was limited to a single experimental setup. Additionally, it did not include a comparison of multiple models. Performance was assessed using F1 score and area under the receiver operating characteristic (AUROC) metrics.

Urbaniak and Ilona Anna[6]: The sensitivity of the DL model to high-frequency content loss caused by compression and its implications for diagnostic interpretation are covered in further detail in this paper. Focuses on DL and JPEG/JPEG2000 but lacks explicit mention of classification tasks or specific CT, MRI, and PET datasets.

Kurmukov, and etil[7]: The study uses Unet models to analyze segmentation tasks and finds cross-domain resilience and no performance degradation up to 20x compression. Incorporates deep learning, JPEG2000 compression, CT and MRI, and focuses on segmentation rather than classification.

V. CONTRIBUTION

This study provides key insights into the impact of image compression on machine learning models for medical imaging. First, it highlights the trade-off between compression levels and model accuracy, helping to optimize compression ratios for reliable classification in resource-constrained environments. Second, it identifies models, such as Logistic Regression and Artificial Neural Networks, that remain resilient to compression artifacts, offering practical guidance for selecting algorithms in telemedicine and AI-driven diagnostic workflows.

VI. METHODOLOGY

The research method consists of multiple Stages as it illustrates in next points and shows in fig 3.

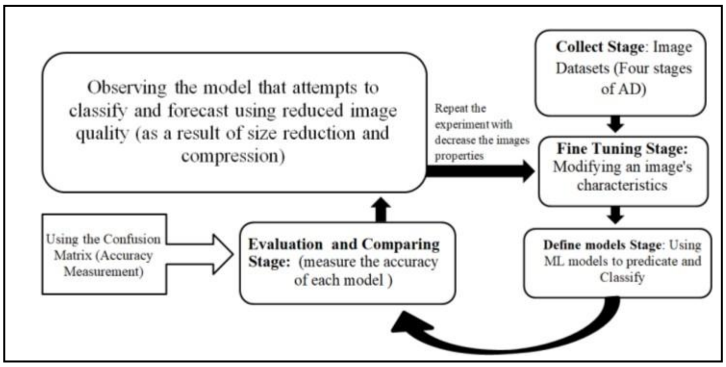

Fig.3.The Methodology With Stages

Collect Stage: consist of original dataset about the brain of AD with four stages are Non-Demented, Mild Demented, Very Mild Demented, and Moderate Demented.

Fine-Tuning Stage: At this step, pre-processing and the production of new data sets are taken into consideration. These are based on making changes to the original datasets about the degree of compression quality and image size to produce three distinct datasets for the tests. Table I shows the three types of datasets have variance in size and image compression ratio.

TABLE I. THE DATASETS USED IN THESE STUDY

Experiment No	Dataset Name	Image No	Image Type	Image Size	Compression Ratio(CR)/Quality
1	Alzheimer-Original-176-208	5789	JPEG	176*208	Acceptable quality for model's Training
2	Alzheimer-320-240	5789	JPEG	320*240	50% Quality
3	Alzheimer-90-10075	5789	JPEG	100*75	0% Quality (Degraded)

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Fig 4 illustrates a representative sample from the original dataset alongside corresponding images subjected to varying levels of compression. The first sample demonstrates the image quality after moderate compression at 50%, while the second depicts the severe degradation resulting from maximum compression, reducing the quality to 0%. This highlights the significant impact of extreme compression on image fidelity and visual clarity.

a b a c

Fig 4. (a) Sample of Original Dataset, (b) Image After Compression 50% and (c) Degraded Image /Zero Quality

Model Definition Stage: Build and train the models to use in the experiments. In the research work logistic regression(LR), decision tree (DT), k-Nearest neighbor (KNN), support vector machine (SVD), and neural network (NN) are selected from traditional machine learning models.

Evaluation and comparing Stage: the results in this stage of all five models are compared and show the assessment by using confusion matrix and then visualize the statistical results.

VII. EXPERIMENTS

As shown in Table 2, this study consists of three experiments based on various datasets. The steps listed below are followed in each experiment.

1. Import the dataset as a readable folder.
2. Images imbedding(convert each image to vectors included image features).
3. To split the dataset into training and testing (in this work the Cross Validation with 10 fold methods was used).
4. Model's Learning
5. To evaluate all model's performance in all experiment using Confusion Matrix based on: Precession, Recall, Accuracy and F-Score.

VIII. RESULTS AND COMPARISON

The results across first experiment which are in Table II show that the Artificial Neural Network achieved the best performance with an accuracy of 0.870, followed by KNN at 0.836. SVM showed moderate results (0.754), while Logistic Regression and Decision Tree performed poorly, with Decision Tree being the least effective (0.593). These findings emphasize ANN's superiority for classification tasks in this context.

TABLE II. RESULTS OF THE FIRST EXPERIMENT OF FIVE MODELS

Model	Accuracy	F-score	Precision	Recall
Logistic- Regression	0.716	0.716	0.716	0.716
Decision -Tree	0.593	0.592	0.592	0.593
K-Nearest Neighbour	0.836	0.834	0.836	0.836
Support Vector Machine	0.754	0.753	0.759	0.754
Artificial Neural Network	0.870	0.870	0.870	0.870

The results reveal poor performance across all models in the second experiment, with Logistic Regression achieving the highest accuracy (0.463) but low precision (0.336) and F-score (0.361). KNN and SVM showed slightly better precision (0.251 and 0.388, respectively) but performed poorly overall. ANN and Decision Tree yielded the lowest performance across all metrics. These findings highlight significant challenges in achieving reliable classification across both experiments as presented in table III.

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TABLE III. THE RESULTS OF THE SECOND EXPERIMENT OF FIVE MODELS

Model	Accuracy	F-score	Precision	Recall
Logistic- Regression	0.463	0.361	0.336	0.463
Decision -Tree	0.101	0.117	0.140	0.101
K-Nearest Neighbour	0.247	0.249	0.251	0.247
Support Vector Machine	0.259	0.287	0.388	0.259
Artificial Neural Network	0.208	0.201	0.194	0.208

The results show suboptimal performance across all models in third experiment Logistic Regression showed the best accuracy (0.455) but had moderate F-score (0.383) and precision (0.363). KNN (accuracy: 0.251) and SVM (accuracy: 0.223) had slightly better precision but lower overall performance. Decision Tree (accuracy: 0.121) and ANN (accuracy: 0.226) were the weakest models as shows in table IV.

TABLE IV. THE RESULTS OF THE THIRD EXPERIMENT OF FIVE MODELS

Model	Accuracy	F-score	Precision	Recall
Logistic- Regression	0.455	0.383	0.363	0.455
Decision -Tree	0.121	0.138	0.162	0.121
K-Nearest Neighbour	0.251	0.270	0.293	0.251
Support Vector Machine	0.223	0.257	0.387	0.223
Artificial Neural Network	0.226	0.217	0.209	0.226

IX. CONCLUSION

The experiments demonstrated that the performance of machine learning models in classifying medical images, especially Alzheimer's disease, is significantly influenced by image compression rates. While models like Logistic Regression and Artificial Neural Networks showed resilience to moderate compression, others such as Decision Trees and K-Nearest Neighbors struggled under the same conditions. The findings highlight the trade-off between compression levels and model accuracy, indicating that careful selection of compression ratios can preserve diagnostic reliability in resource-constrained settings. These results are particularly relevant for applications like telemedicine and AI-based diagnostic tools in healthcare.

X. FUTURE WORK

Future research will explore more image affections, such as noises, blurring, low resolution, etc., and their effects on various deep-learning architectures, especially in high-stakes medical applications. Additionally, expanding the dataset to include diverse medical imaging conditions would enhance model generalizability. Also, investigating hybrid models that combine low-quality image-aware algorithms with state-of-the-art neural networks could lead to more efficient and accurate diagnostic systems in low-bandwidth environments.

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