Early Diagnosis and Classification of Alzheimer's Disease Using Convolutional Neural Network based on MRI Images

***Abstract*—Alzheimer's disease (AD) is a progressive neurodegenerative disorder that affects memory, thinking, and behavior, gradually leading to mild to severe dementia. Over the past decade, researchers have leveraged deep learning models, such as Convolutional Neural Networks (CNN) and transfer learning, for the early detection and classification of AD. In this paper, we propose a simple and computationally cost-effective CNN architecture for the early diagnosis and classification of AD. The model was trained using ADNI T1-weighted 2D MRI scans, encompassing cognitively normal (CN) individuals, stable mild cognitive impairment (sMCI) cases, and Alzheimer's dementia (AD) patients. Experimental results demonstrate the superiority of our model, achieving an accuracy of 98.97%, thereby surpassing most previous studies while utilizing a low-cost custom CNN architecture.**

***Index Terms*—Alzheimer's disease (AD), Convolutional neural network (CNN), ADNI, SMOTE**

I. Introduction

Alzheimer's disease (AD), the most prevalent form of dementia, poses a significant public health challenge, with no recognized therapy capable of modifying its progression. The onset of AD is often insidious, gradually advancing over several years before clinical symptoms manifest [1]. Currently, it is estimated that over fifty million people worldwide are affected by AD and other dementia-related conditions [2]. In the United States alone, approximately seven million individuals were living with AD as of 2022, with projections suggesting this number will double to fourteen million by 2050 [3]. The growing prevalence of AD and related conditions, such as mild cognitive impairment (MCI), underscores the urgent need for innovative early diagnostic methods to facilitate timely intervention and potentially halt disease progression.

Recent advancements in machine learning and deep learning have shown promise in the early detection and classification of AD [4] [5] [6]. Various models have been explored in numerous research projects to improve diagnostic accuracy. Shahbaz et al. [7] incorporated machine learning algorithms such as KNN, Decision Trees, Rule Induction, Naïve Bayes, Generalized Linear Model (GLM), and Deep Convolutional Neural Networks (DCNN). Convolutional Neural Network (CNN) models have also been widely used in studies by [8]–[12]. Additionally, Islam and Zhang [13] and Hon and Khan [14] applied the Inception V4 model, while Acharya et al. [15] employed a combination of VGG16, ResNet-50, and AlexNet as transfer learning models along with CNN.

Despite these advancements, several challenges remain. For example, Islam and Zhang [13] reported a 73.75% accuracy in AD detection using the Inception V4 model, indicating room for improvement. Kundaram and Pathak [8] achieved a 98.57% accuracy with Deep CNN but highlighted the need for better interpretability of the deep learning models and comparisons with other architectures. Shahbaz et al. [7] achieved an accuracy of 88.24% using GLM, which is relatively lower compared to other studies. Ji et al. [9] attained a 97.65% accuracy using ensemble learning with CNN, though the study was limited by a small dataset. Hon and Khan [14] employed VGG16 and Inception V4 to achieve a 92.3%, 96.25% accuracy using VGG16 and Inception V4, respectively, while Raza et al. [10] achieved 97.84%accuracy using CNN with transfer learning. Acharya et al. [15] introduced an AD classification approach with 95.70% accuracy using a combination of VGG16, ResNet-50, and AlexNet, but did not explore other imaging modalities or data sources that could potentially enhance the classification accuracy. Agarwal et al. [4] utilized EfficientNetB0 and achieved 93.10% of accuracy. Lu and Popuri et al. [6] introduced multiscale deep neural network and obtained 82.51% accuracy. Ibrahim et al. [5] achieved an accuracy of 98.50% using CNN.

The main contributions of this article is as follows:

- We propose a cost-effective CNN architecture
- We preprocessed MRI scans using Pydicom library
- We trained the proposed CNN architecture using preprocessed MRI scans to classify CN, SMCI, and AD stages

The rest of this article is structured as follows: Section II provides an overview of the dataset, detailing our research approach, data preprocessing methods, the proposed CNN architecture, and the justification for our procedural architecture. Section III discusses the evaluation measures, experimental setup, performance analysis for both training and validation data, and performance analysis for test data. Section **??** considers potential threats to the validity of the results. Finally, section V summarizes our findings, and section VI, suggest future research directions and followed by references.

II. Methodology

A. Sequential workflow of the proposed methodology

Our research approach focuses on developing a simple yet effective CNN architecture for the early detection and classification of Alzheimer's disease. The primary objective

is to achieve high classification accuracy while maintaining computational efficiency. The approach involves several key steps: data preprocessing, model design, training, and evaluation.

We used the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset, an open source dataset for classification of different alzheimer's stages. Comprehensive preprocessing procedures, as described in Section II-C, were performed on the ADNI dataset to improve the quality of the dataset. The preprocessed dataset was then partitioned into training (70%), validation (10%), and test (20%) sets. This partitioning approach, aligned with established best practices, facilitated comprehensive model training, validation, and evaluation procedures—essential for ensuring the efficacy and generalizability of the developed model. Next, our proposed Convolutional Neural Network (CNN) model was implemented and underwent rigorous training iterations, leveraging the training dataset to optimize parameter adjustments aimed at minimizing training loss and enhancing overall performance metrics. Throughout this process, the validation dataset was integral to assessing the model's generalizability. It facilitated the iterative refinement of hyperparameters, ensuring the model's robustness and optimal performance. A thorough evaluation of the trained CNN model was performed using the test data employing different evaluation metrics such as accuracy, precision, recall, and F1-score.

Figure 1 illustrates the workflow of our study, from data collection through model training to evaluation. It provides a clear visualization of the sequential processes involved in our research methodology.

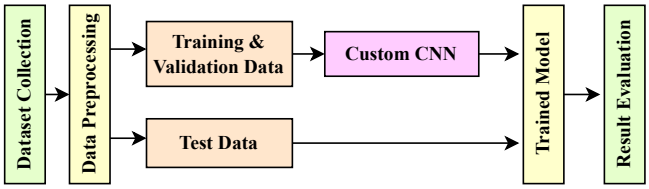

Fig. 1. Sequential workflow of the proposed methodology

B. Dataset Description

The dataset utilized in this study was collected from the Alzheimer's Disease Neuroimaging Initiative (ADNI) database, an open source dataset that is freely available on ADNI website [16]. We used 1584 T1-weighted (T1W) 2D MRI scans, 968 of CN subjects, 144 of sMCI subjects, and 130 of AD subjects, all acquired in DICOM format. The summary of the ADNI dataset is presented in the Table I.

TABLE I
SUMMARY OF THE DATASET

No of Images	Format	No of Classes	Source
1584	TIFF	3	ADNI

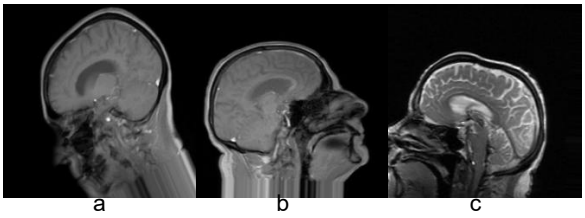

Fig. 2. Sample images for each class

C. Data Preprocessing

Each of the ADNI MRI scans, originally in DICOM format—a standard digital medical imaging format—was converted into TIFF format using Python libraries pydicom and imageio to streamline the model training process, optimizing efficiency and cost-effectiveness. To ensure consistency and reliability in subsequent analyses, we implemented a crucial step of normalization to mitigate potential covariate shifts that could skew results. Additionally, a label encoder was utilized to seamlessly integrate categorical data into numerical models, facilitating a smooth transition from categorical class labels to numerical representations. To address the challenge of class imbalance, we employed the Synthetic Minority Oversampling Technique (SMOTE). This technique effectively mitigated class imbalances, thereby enhancing the robustness and representativeness of the dataset, crucial for accurate model training and evaluation.

In preparation for model training and evaluation, additional preprocessing steps were meticulously executed. This included reshaping the images to (224, 224, 3) dimensions, ensuring uniformity and compatibility for streamlined processing and rigorous analysis. Finally, the dataset was partitioned into separate subsets for training (70%), validation (10%), and testing (20%), following best practices in data splitting to ensure thorough and reliable model evaluation.

D. Architecture of the proposed CNN model

Our methodology begins with meticulous preprocessing of input images, transforming them into tensor representations to optimize compatibility with our custom CNN architecture. Central to our model design are three convolutional blocks carefully engineered to extract hierarchical features from the input images. These convolutional blocks—comprising 16, 32, and 64 filters—incrementally enhance the depth of feature representation essential for capturing intricate patterns indicative of Alzheimer's disease stages.

Each convolutional block is supplemented with a MaxPooling2D layer, strategically placed to downsample feature maps while preserving critical spatial information. Rectified Linear Unit (ReLU) activation functions are applied across all convolutional layers to introduce non-linearity, crucial for mitigating the vanishing gradient problem and enhancing feature propagation.

Following the convolutional layers, the output undergoes flattening, transforming multi-dimensional feature maps into

a one-dimensional array. This flattened representation seamlessly integrates into subsequent fully connected layers, which further refine extracted features through additional non-linear transformations using ReLU activation functions. The architecture's design incorporates a flattened layer to optimize the transition from spatially rich representations to the streamlined format required by dense layers, thus optimizing computational efficiency.

At the final layer, a softmax activation function computes multi-class probabilities, enabling the model to generate probabilistic predictions across multiple disease stages simultaneously. To mitigate overfitting and enhance generalization, a Dropout layer with a dropout rate of 0.5 is strategically inserted between the dense layers. This dropout mechanism selectively deactivates neurons during training, thereby improving the model's robustness to noise and variability in input data, crucial for reliable diagnostic performance.

Figure 3 provides a comprehensive architectural overview of our proposed CNN model, illustrating the sequential flow from initial input preprocessing to final output prediction. This schematic representation encapsulates the functional elements and structural design of our CNN architecture, underscoring its suitability for robust and efficient classification tasks in medical imaging, particularly in the early detection and classification of Alzheimer's disease.

E. Experimental setup

The architectural operations for our model were conducted on Kaggle, leveraging two NVIDIA Tesla T4 GPUs. These GPUs are based on the Turing architecture and are equipped with 15 GB of GDDR6 memory each. Each T4 GPU features 2,560 CUDA cores, which significantly accelerate the deep learning computations. The CPU used was a 2-core Intel Xeon with 29 GB of RAM and a maximum disk size of 73.1 GB, providing robust support for data processing and model training.

The input images were resized to dimensions of 224x224x3 to standardize the data and ensure compatibility with the model architecture. The dataset was partitioned into training, validation, and testing sets with a ratio of 70%-10%-20%, respectively, providing a comprehensive framework for model evaluation. The training and validation processes employed the Adam optimizer with a learning rate of 0.001 and categorical cross-entropy as the loss function. The model was trained for 34 epochs, with batch sizes of 4. To prevent overfitting and enhance model generalization, early stopping was implemented using the ReduceLROnPlateau callback, with patience values set at 15. This strategy dynamically reduced the learning rate when a plateau in validation loss was detected, optimizing the training process.

F. Justification of Our Procedural Architecture

Our procedural architecture employs three convolutional layers with kernel sizes of 3x3 and varying depths of 16, 32, and 64 filters. This deliberate choice results in a lightweight model that achieves optimal performance with a reduced number of parameters. Consequently, our model requires less training time and computational resources compared to state-of-the-art approaches in Alzheimer's disease classification. This efficiency not only enhances practical usability but also underscores our commitment to developing cost-effective solutions without compromising on accuracy or reliability in medical image analysis.

III. Result And Performance Analysis

A. Evaluation Measures

To evaluate the performance of our proposed CNN model, we used four key metrics: accuracy, precision, recall, and F1-score. These metrics help assess how well the model distinguishes between cognitively normal (CN), stable mild cognitive impairment (sMCI), and Alzheimer's dementia (AD) categories. The evaluation metrics are defined as follows [17]:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{4}$$

$$Specificity = \frac{TN}{TN + FP} \tag{5}$$

Here, TP (True Positives) is the number of correctly predicted positive instances, TN (True Negatives) is the number of correctly predicted negative instances, FP (False Positives) is the number of incorrectly predicted positive instances, FN (False Negatives) is the number of incorrectly predicted negative instances [18].

Accuracy measures the overall correctness of the model. Precision indicates the proportion of correct positive predictions. Recall (Sensitivity) measures the ability to identify all true positive cases. F1-Score is the harmonic mean of precision and recall, providing a balanced measure. These metrics were calculated for each class (CN, sMCI, and AD) to ensure a comprehensive evaluation. This multi-metric approach helps identify the model's strengths and areas for improvement, guiding future enhancements.

B. Performance analysis for training And validation dataset

Figure [4 illustrates the evolution of training and validation losses, as well as accuracy, across successive epochs. This analysis highlights the model's learning dynamics, demonstrating how performance metrics improve over time as the model adapts to the data.

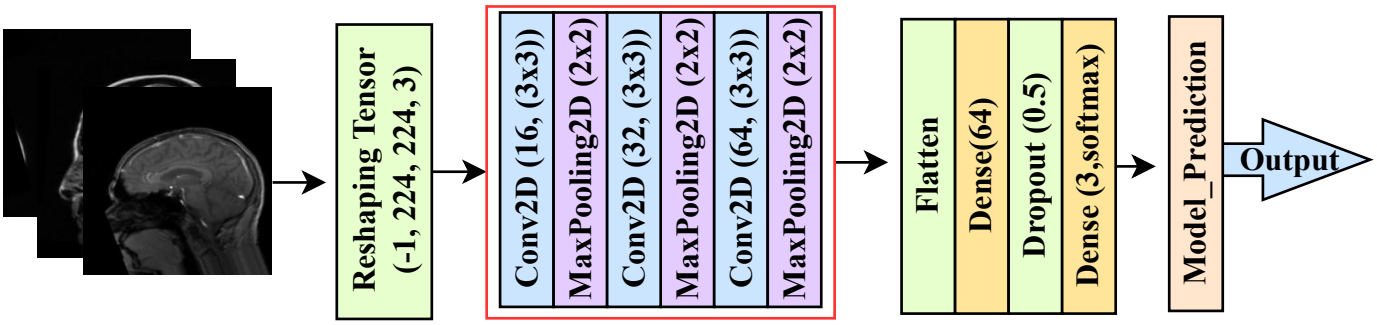

Fig. 3. Architectural view of the proposed methodology

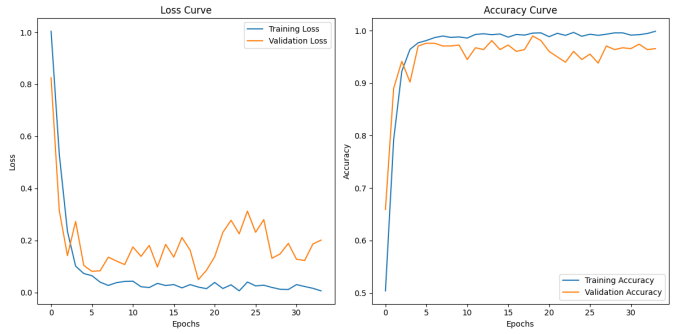

Fig. 4. Loss and accuracy curve for the proposed CNN model

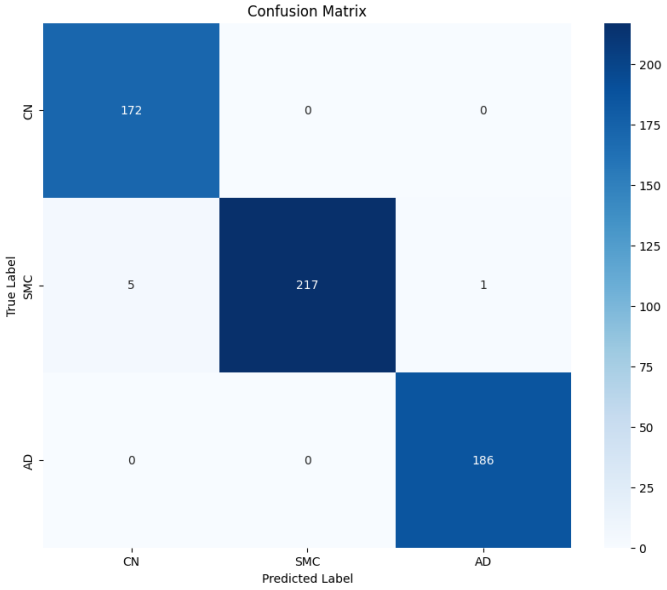

Fig. 5. Confusion matrix for the proposed CNN model

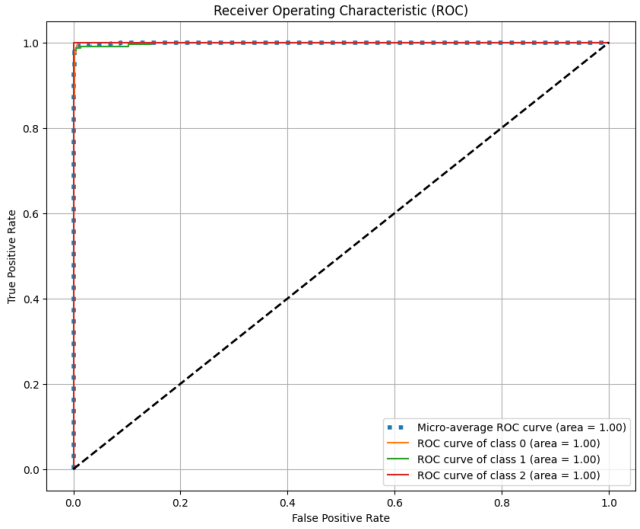

Fig. 6. ROC-AUC Curve for the proposed CNN model

C. *Performance analysis for test dataset*

We conducted a comprehensive analysis of our proposed model's performance using the unseen test data to evaluate its predictive accuracy and robustness. Training the model with a batch size of 4 over 34 epochs, our custom CNN architecture achieved remarkable results. The model attained an accuracy of 98.97%, a precision of 98.99%, a recall of 98.97%, and an F1-score of 98.97%. These metrics underscore the model's high effectiveness and reliability in classifying Alzheimer's disease stages. Figure 5 llustrates the confusion matrix for the test data, providing a detailed visual representation of the model's classification performance.

The performance of our model is further highlighted by the ROC-AUC curve presented in Figure 6. These curve graphically demonstrate the architecture's convergence. The true positive rate and false positive rate exhibit minimal volatility, resulting in nearly straight lines. This indicates that our model achieves steady and reliable convergence.

IV. Discussion

Table II presents a comprehensive comparison demonstrating that our final results significantly outperform most of the previous research efforts. Our proposed model, despite its simplicity, has demonstrated superior capabilities, confirming its efficacy in Alzheimer's disease diagnosis and classification.

TABLE II
PERFORMANCE COMPARISON WITH PREVIOUS STUDIES

Classifier	Accuracy%	Precision%	Recall %	F1 score%
Inception-V4 [13]	73.75	-	-	-
DCNN [8]	98.57	-	-	-
GLM [7]	88.24	-	-	-
CNN [9]	97.65	-	-	-
Inception V4 [14]	96.25	-	-	-
TL [10]	97.84	-	-	-
AlexNet [15]	95.7	91.9	92.3	94.7
EfficientNetB0 [4]	93.10	86.38	87.51	86.43
MDNN[13] [6]	82.51	-	-	-
Ours	**98.97**	**98.99**	**98.97**	**98.87**

V. CONCLUSION

In this study, our primary objective was to advance the diagnosis and classification of Alzheimer's disease (AD) using convolutional neural network (CNN). The accurate and automated classification of AD is critical for improving patient outcomes and driving advancements in neurodegenerative disease research. Our research focused on developing and optimizing a customized CNN model specifically designed for AD classification from MRI scans. Through rigorous experimentation, our CNN model consistently met our study's initial hypotheses, demonstrating robust performance and highlighting the pivotal role of automated AD categorization in clinical practice. This approach offers a more efficient and accurate alternative to traditional manual methods, paving the way for enhanced diagnostic capabilities and early intervention strategies. Looking ahead, further refinement of model architectures and data preprocessing techniques promises to bolster the reliability and applicability of AD classification systems in real-world healthcare settings, ultimately contributing to improved patient care and management of neurodegenerative diseases.

VI. FUTURE SCOPE

Future work will focus on developing more efficient methodologies that reduce training time and simplify the process. We aim to integrate our model into mobile devices using federated learning techniques, creating a decentralized, automated system for classifying Alzheimer's Disease (AD). Federated learning will enhance data privacy and security while improving the model's robustness and generalizability. This approach will enable real-time updates and continuous learning, crucial for medical diagnostics. Additionally, we plan to enhance model generalizability by merging various publicly available datasets for more accurate prediction of AD stages.

REFERENCES

[1] J. Hardy, "Amyloid, the presenilins and alzheimer's disease," *Trends in neurosciences*, vol. 20, no. 4, pp. 154–159, 1997.

[2] C. Patterson, "World alzheimer report 2018," 2018.

[3] A. Association *et al.*, "2018 alzheimer's disease facts and figures," *Alzheimer's & Dementia*, vol. 14, no. 3, pp. 367–429, 2018.

[4] A. L. Deevyankar Agarwal, Manuel Álvaro Berbís, "Automated medical diagnosis of alzheimer´s disease using an efficient net convolutional neural network," in *Journal of Medical Systems*, vol. 47, no. 57. Springer, 2023.

[5] R. G. Rahmeh Ibrahim and Q. A. Al-Haija, "Improving alzheimer's disease and brain tumor detection using deep learning with particle swarm optimization." mdpi, 2023.

[6] P.-K. D. G. W. B. R. B. M. F. Lu, D., "Alzheimer's disease neuroimaging initiative. multiscale deep neural network based analysis of fdg-pet images for the early diagnosis of alzheimer's disease," in . *Med. Image Anal*, vol. 46. ELSEVIER, 2018, p. 26–34.

[7] M. Shahbaz, S. Ali, A. Guergachi, A. Niazi, and A. Umer, "Classification of alzheimer's disease using machine learning techniques." in *Data*, 2019, pp. 296–303.

[8] S. S. Kundaram and K. C. Pathak, "Deep learning-based alzheimer disease detection," in *Proceedings of the Fourth International Conference on Microelectronics, Computing and Communication Systems: MCCS 2019*. Springer, 2021, pp. 587–597.

[9] H. Ji, Z. Liu, W. Q. Yan, and R. Klette, "Early diagnosis of alzheimer's disease using deep learning," in *Proceedings of the 2nd international conference on control and computer vision*, 2019, pp. 87–91.

[10] N. Raza, A. Naseer, M. Tamoor, and K. Zafar, "Alzheimer disease classification through transfer learning approach," *Diagnostics*, vol. 13, no. 4, p. 801, 2023.

[11] A. Nawaz, S. M. Anwar, R. Liaqat, J. Iqbal, U. Bagci, and M. Majid, "Deep convolutional neural network based classification of alzheimer's disease using mri data," in *2020 IEEE 23rd International Multitopic Conference (INMIC)*. IEEE, 2020, pp. 1–6.

[12] A. Farooq, S. Anwar, M. Awais, and S. Rehman, "A deep cnn based multi-class classification of alzheimer's disease using mri," in *2017 IEEE International Conference on Imaging systems and techniques (IST)*. IEEE, 2017, pp. 1–6.

[13] J. Islam and Y. Zhang, "A novel deep learning based multi-class classification method for alzheimer's disease detection using brain mri data," in *Brain Informatics: International Conference, BI 2017, Beijing, China, November 16-18, 2017, Proceedings*. Springer, 2017, pp. 213–222.

[14] M. Hon and N. M. Khan, "Towards alzheimer's disease classification through transfer learning," in *2017 IEEE International conference on bioinformatics and biomedicine (BIBM)*. IEEE, 2017, pp. 1166–1169.

[15] H. Acharya, R. Mehta, and D. K. Singh, "Alzheimer disease classification using transfer learning," in *2021 5th International Conference on Computing Methodologies and Communication (ICCMC)*. IEEE, 2021, pp. 1503–1508.

[16] "Alzheimer's dataset," https://adni.loni.usc.edu/, (Accessed on 12/10/2023).

[17] N. Haque, A. H. Efat, S. M. Hasan, N. Jannat, M. Oishe, and M. Mitu, "Revolutionizing pest detection for sustainable agriculture: A transfer learning fusion network with attention-triplet and multi-layer ensemble," in *2023 26th International Conference on Computer and Information Technology (ICCIT)*. IEEE, 2023, pp. 1–6.

[18] N. Haque, R. Toufiq, M. Z. Islam, and M. A. A. T. Shoukhin, "Garbage classification using a transfer learning with parameter tuning," in *2024 6th International Conference on Electrical Engineering and Information & Communication Technology (ICEEICT)*. IEEE, 2024, pp. 1252–1256.