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Original Article

EBiGRU: An Enhanced Bidirectional GRU-Based Multi-scale Neural Network for Intelligent Waste Segregation

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Abstract - *The demand for effective waste management systems increases with evolving technology, and an intelligent system is needed to classify and segregate waste easily and optimally. With this focus, this paper proposes a novel method of waste classification that utilizes the benefits of Convolutional Neural Networks (CNN) to improve the performance of Bidirectional Gated Recurrent Units (BiGRU) and develop an Enhanced BiGRU (EBiGRU). Here, a novel Multi-Scale Linear Aggregation Network (MLAN) in CNN is a backbone for BiGRU and extracts scale-invariant features to understand the local and global context of the information in the captured images. These feature maps are then sequentially embedded with customized BiGRU to define the dependencies between forward and backwards directions. This combination not only improves the feature representation but also enhances contextual awareness and makes the model robust to scale variations. The proposed system is evaluated using two separate datasets (Waste Segregation Image and Garbage Classification dataset) and one with their combination. The performance is computed based on accuracy, loss, and correct classification rate, which declares the efficacy of the proposed method and presents its robustness.*

Keywords *- Waste classification, Deep Learning, BiGRU, EBiGRU, Multi-scale features.*

1. Introduction

The growth of technology and advancements in Artificial Intelligence (AI) have introduced different cutting-edge technologies to our daily lives. These advancements have provided intelligent and automated solutions for different problems. From different application areas, waste management is the prominent application that needs automation for different related tasks (Fatimah et al., 2020). This application area also requires resource efficiency to advance the process of waste collection or recycling. The population growth and increase in waste also raise a lot of complexities in the existing waste management systems. Nowadays, based technologies are included to offer better solutions and provide simple but effective systems (Cheema et al., 2022). With this aim, the proposed research work also incorporates AI with waste management systems and introduces an efficient and intelligent system for waste segregation.

Most of the existing real-world waste management systems are handled manually, and human labourers are involved in the process of collection, sorting, etc. Though this method is not physically hard, toxic waste materials such as chemicals, medical waste, etc., can badly affect the health of workers. This can also lead to reduced accuracy and recycling rates (Andeobu et al., 2022). The overall efficacy of the manual systems is also lower due to the bias factor and demands a better system for the task of waste classification (Salem et al., 2023).

AI-based technologies can be one of the possible solutions for providing an effective system for waste classification. Different algorithms of AI, such as Machine Learning (Ml), Neural Networks (NN), etc., can help automate this manual process by recognizing and classifying different waste materials. Computer vision technology uses image- or video-based data and integrates AI algorithms to provide a better and more precise system (Strollo et al., 2020). Also, it helps reduce human involvement and provides a more sustainable solution for waste classification systems. AI-based devices or approaches with computer vision resolve safety and health issues and boost recycling rates, which is a critical aspect in the field of Waste Management System (Sharma, 2023). Nowadays, Deep Learning (DL) methods with computer vision play a significant role in advancing various systems, so it can also be opted for in waste management systems (Malik et al., 2022). DL methods train the models with deeper layers, extract relevant feature information automatically, and process it at the end layer. Mainly, DL methods use Convolutional Neural Networks (Cnns) or Recurrent Neural Networks (RNNs) to extract complex feature information and derive possible solutions. This research study also aimed to include the DL approach for enhancing the abilities of the existing systems.

1.1. Motivation

This research work aims to enhance the existing AI-aided architecture for the problem of waste segregation. Based on recent developments, DL methods have found optimistic results in different image classification tasks, including waste segregation. While CNNs are proficient at extracting spatial information, they often lack in modeling temporal dependencies. On the other hand, RNN-based architectures can learn temporal or sequential patterns but fail in extracting spatial information. In order to increase the efficiency of the existing systems, the challenges, such as scale variations, contextual richness, etc., which are essential components, need to be considered while designing DL architectures. So, to bridge the gap between the existing challenges, this research proposes a novel enhanced bidirectional GRU-based multi-scale neural network. The detailed contribution in terms of novelty is discussed in the next sub-section.

1.2. Contribution of the Paper

The focus of this paper is to develop an intelligent waste segregation method, based on which the contributions of the paper are:

- *Design and Development of an Enhanced Deep Learning Architecture for Waste Segregation:* This research proposes an Enhanced Bidirectional GRU (EBiGRU) that integrates CNN to effectively capture spatial and sequential patterns from the waste images and improve the overall accuracy of the segregation system.
- *Novel Multi-Scale Linear Aggregation Network (MLAN) in CNN:* By providing scale-invariant features, MLAN enhances the information of the object(s) present in an image and also handles the object's variable size. These features enrich the data and hence improve the performance of the proposed system.
- *Feature Embedding with Bidirectional Learning:* The sequential patterns of BiGRU allow learning in both forward and backwards directions and hence improve the contextual understanding to improve the classification decisions.

The following sections of this article go into critical areas of the research, offering a thorough examination of the subject. Section 2 analyze the existing studies in the domain of waste classification using traditional as well as learning-based approaches. Section 3 provides the detailed methodology of the work, including dataset details, different methods, all the setups for experimentation, etc. Section 4 is the experimentation section that details experimentation and outcomes from the implementation and compares them with existing studies. The final section is a conclusion that provides concluding remarks and future visions.

2. Related Work

The related work section mainly covers the details of the existing studies. In this work, the main aim is to classify the waste based on the existing studies that have been selected. Relevant resources, including journals and conference contributions, are discussed along with their gaps. The study situates the suggested model within the larger landscape of waste management technology by critically reviewing existing studies. This comprehensive overview educates the reader on state-of-the-art waste segregation and highlights the distinctive contributions and innovations made by the remaining sections of the article.

In recent years, growing global concern about the environmental impact of incorrect waste disposal has fuelled an increase in R&D projects. The increasing volume of garbage created, which is frequently disposed of in ecologically harmful ways, has forced a rethinking of waste management procedures. Both the industrial and home sectors contribute considerably to this growing problem. However, a lack of attention on waste separation at the source, notably in families, has resulted in the neglect of industrial waste. V.P. et al. (V.P. et al., 2020) addressed this essential issue by emphasizing industrial waste segregation and designing a low-cost intelligent bin system. They have targeted small and medium-sized industries that mainly contribute to metallic and non-metallic waste, such as electronic circuits or microprocessors, etc. and designed a classification system for them in order to segregate the waste efficiently.

A low-cost automated waste classification system was developed by Sunehra et al. (Sunehra et al., 2021) to classify the waste into moist, metallic and dry for both plastic and paper waste. They built a model prototype using an Arduino Uno board and sensors that recognizes the waste material and also segregate it. Another waste segregation system named SWS was designed by Rakib et al. (Rakib et al., 2021) to monitor and classify wet and dry waste. They have used different sensors, including ultrasonic and moisture sensors, and an alert system using GSM services to notify the authorities of the waste level.

Another system with ultrasonic sensor, color sensor, servo motors, etc., was designed by Leo et al. (Megalan Leo et al., 2022) to classify the biodegradable and non-biodegradable waste. A similar classification system was designed by Nair et al. (Nair et al., 2023), in which they also utilized cloud infrastructure for transferring visual data and analyzing it. Then this analysis was sent back to the hardware unit, and the appropriate bin was selected for the waste material. Another hardware module was designed by Shreeshayana et al. (Shreeshayana et al., 2022) to separate dry and wet waste. They also added a composite unit to convert the organic waste into compost. All these are sensor-based solutions that are not cost-friendly and affordable for the general population.

Apart from these sensor-based solutions, an intelligent solution using DL-based algorithms has also been introduced over the past few years and is discussed here in this section. A single-shot detector and a mobilenet architecture were proposed by Koganti et al. (Koganti et al., 2021) for the segregation of biodegradable and non-biodegradable waste. They also designed a hardware prototype using a camera and a Raspberry Pi to identify the waste and put it into the bin accordingly. This architecture is purely a CNN architecture and learn through spatial information. Hence, it lacks contextual understanding and is less accurate, specifically for small objects in the image frame. Another DL based approach was designed by Kapadia et al. (Kapadia et al., 2021) to classify dry waste, including cans and bottles. This research mainly focuses on classifying solid waste, such as cans, bottles, etc. The performance of this architecture is comparatively better, but needs validation with other classes of waste.

The integration of learning methods in hardware units was designed by Parvin et al. (Parvin et al., 2022) for automatic identification and classification of waste materials. In the hardware unit, an infrared sensor was used to detect the blockages, based on which a Raspberry Pi triggers the DC motor for forward rotation, and accordingly, the conveyor belt moves. With this belt, a sensor was attached that can identify the type of waste. The DL method embedded in the Arduino Uno with different sensors was designed by Kavithamani et al. (A et al., 2023) to measure the level of the filled bin and automatically open and close based on user proximity. The deep CNN architecture was designed by Nafiz et al. (Nafiz et al., 2023) for the accurate classification of waste. An ultrasonic sensor, GSM connectivity, a remote control unit, and an Android application were designed to provide a cost-efficient solution for the same. With advancements, DL architectures are able to detect waste material and classify it. A YOLOv5 architecture was used (Puthussery et al., 2023) for the detection of waste and its classification with good accuracy. They also used a motorised conveyor belt and integrated this architecture into a hardware unit. This effective trash sorting technology promises not just speedier recycling, but also time and resource savings.

An IoT and ML-based most recent development in automatic waste segregation effectively helps in waste management (Chavhan et al., 2023). The main aim of this system was to automate waste segregation and improve the recycling rates. In this, a ResNet-101 model achieves an accuracy of 95% which can categorize the waste into organic, recyclable, and non-recyclable materials. However, the additional complexity and overfitting concerns make the ResNet model difficult to train and deploy efficiently in some contexts. While its deep architecture enables outstanding feature learning and representation capabilities, the risk of overfitting emerges when working with small datasets. Furthermore, increasing processing needs may impede real-time applications and deployment on resource-constrained devices.

Most conventional systems have depended heavily on sensor-based technology that increases the cost of the solution and makes a burden on individuals as well as governments. However, the recent incorporation of deep Learning constitutes a huge step forward and adds a new dimension to the continuing evolution. Using only images, these technologies provide efficient solutions in several different application areas, so this proposed research work not only improves the capabilities of existing systems but also provides a cost-friendly solution for Intelligent waste classification systems.

Despite significant improvements in the waste classification system, there is no such system, to the best of the author's knowledge, that uses both spatial and temporal characteristics to train the model and improve the contextual understanding for improving classification decisions. Also, in the existing systems, the lack of multi-scale information reduces the chances of detecting small objects. Based on these limitations, it is clear that the waste classification requires an accurate and robust system to improve the overall efficiency of the waste segregation system.

3. Materials and Methods

The fundamental goal of the research is to develop an intelligent waste segregation system capable of categorizing garbage and determining whether it is biodegradable or non-biodegradable. So, for this work, an EBiGRU architecture that uses the CNN-based backbone for the proposed BiGRU architectures is proposed. The novel MLAN backbone gives several benefits to the proposed architecture for classifying waste using images. This section discusses the details of the novel MLAN and EBiGRU architecture and basic GRU and BiGRU.

3.1. Gate Recurrent Unit (GRU)

With the evolution of deep Learning, which involves using neural networks with numerous layers or deep neural networks, different specialized concepts have been designed to meet specific issues in data processing. Convolutional Neural Networks (CNN) emerge as a significant advancement in deep Learning, intended primarily for processing structured grid data like images. CNNs use convolutional layers to scan and filter incoming data, allowing them to record spatial hierarchies and extract detailed information from images. While CNNs are suitable for grid-like data, Recurrent Neural Networks (RNNs) excel at handling sequential data. RNNs keep a hidden state that changes with each time step, allowing them to detect temporal connections in sequences. However, classic RNNs face long-term dependencies and the vanishing gradient problem. In response to these issues, the GRU was proposed as an improvement to regular RNNs. Cho et al.

introduced the GRU in 2014, which integrates gating features into the network design. These systems control the flow of information, finding a balance between recording long-term relationships and addressing the vanishing gradient problem.

The GRU's functioning is dependent on two fundamental components. Similar to other RNNs, the hidden state changes with each time step in the sequence, acting as the network's memory. This concealed state retains relevant information from previous inputs, allowing a better grasp of context over time. GRU has two critical gating mechanisms: the reset gate (r_i) and the update gate (u_i), as shown in Figure 1.

The reset gate controls the amount to which previous information is discarded in the next time step, allowing the model to adjust to changing data patterns. The update gate, on the other hand, controls how much new information should be absorbed into the current concealed state, allowing for a more selective and nuanced updating of the network's memory. The equations used to compute the reset and update gates are given below:

$$r_i = \sigma(w_r \times [y_{i-1}, x_i]) \tag{1}$$

$$u_i = \sigma(w_u \times [y_{i-1}, x_i]) \tag{2}$$

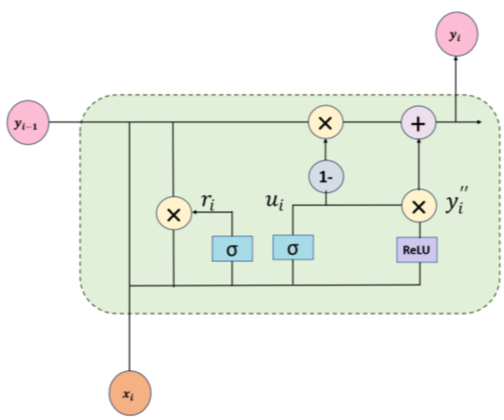


Fig. 1 Schematic diagram of Gated Recurrent Unit

Further, the current hidden state (y_i) is calculated from the candidate hidden state (y_i'), which is computed as:

$$y_i' = tanh(w_y \times [r_i \times y_{i-1}, x_i]) \tag{3}$$

In this work, instead of using the *tanh* activation function, the rectified linear unit (*ReLU*) is used as an activation. Here, the capacity of ReLU to deliver a non-saturated outcome in response to positive inputs helps in supporting the network's continued robust signal propagation. Moreover, ReLU is used for faster training and to improve the model's performance. Therefore, the updated candidate hidden state (y_i'') is computed as follows:

$$y_i'' = ReLU(w_y \times [r_i \times y_{i-1}, x_i]) \tag{4}$$

$$y_i = (1 - u_i) \times y_{i-1} + u_i \times y_i'' \tag{5}$$

In the above equations, w_r, w_u, and w_y are learnable weights, x_i is the input at the i^{th} state, y_{i-1} is the previous hidden state, and y_i is the current hidden state. By employing this gating mechanism, GRUs selectively update the hidden state at each timestep, enabling it to collect and model data patterns accurately.

3.2. Bidirectional GRU

GRUs, like other RNNs, have difficulty collecting contextual information from both past and future sequences while processing sequential data. The underlying difficulty is their potential struggle with long-term dependencies, which limits their capacity to use information in both directions in a sequence fully. These GRUs were then enhanced to provide detailed context awareness by integrating bidirectional processing called BiGRU. In applications such as time series analysis or natural language processing, BiGRUs enhanced the ability of the models by extracting patterns and relationships in the sequence data. In this, two GRU layers, forward and backwards, are shown in Figure 2. One processes the input sequence forward, while the other processes it backwards, computed as follows:

$$y_i^f = (1 - u_i^f) \times y_{i-1}^f + u_i^f \times y_i^{f''} \tag{6}$$

$$y_i^b = (1 - u_i^b) \times y_{i-1}^b + u_i^b \times y_i^{b''} \tag{7}$$

The outputs from both directions are often concatenated, resulting in a complete representation of the input sequence, as shown below.

$$y_i = [y_i^f | y_i^b] \tag{8}$$

3.3. Multi-scale Linear Aggregation Network (MLAN)

In DL-architectures, CNN introduces the feature extraction, which extracts the spatial information at high resolution levels and channel information at lower resolution levels in order to improve the efficiency of the classification systems. By retaining spatial information, a model can make more accurate predictions by understanding the context and structure of the image. So, with this aim, a novel MLAN is proposed that aggregates the output of different convolution layers and extracts scale-invariant features in order to preserve the information of different-sized objects.

As shown in Figure 3, an input image of size (H×W×3) is passed through an initial convolution (Conv) layer of kernel size 3×3 and 'n' kernels to extract C different channel features. For deeper and different feature representations, a Conv layer with stride=2 is then used and extracts 2C, i.e., double the number of features.

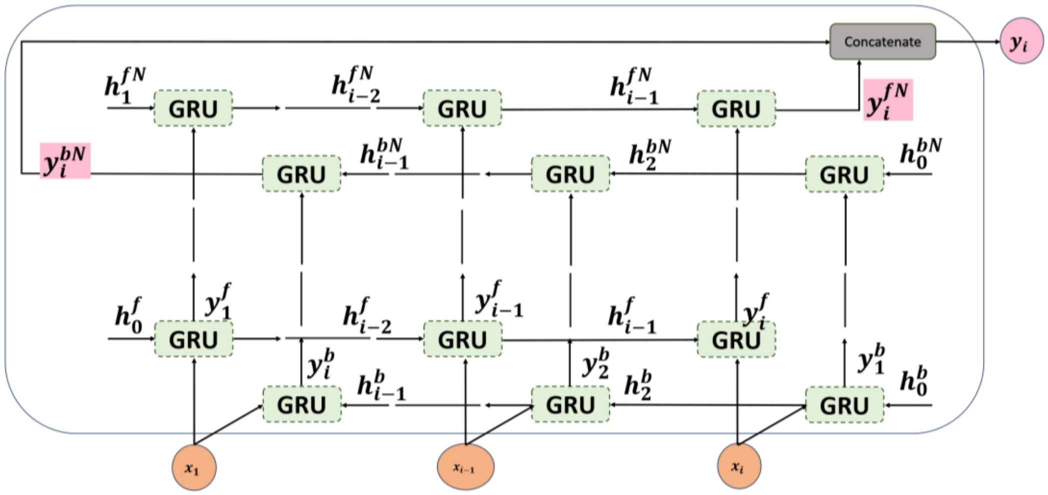


Fig. 2 Schematic diagram of BiGRU

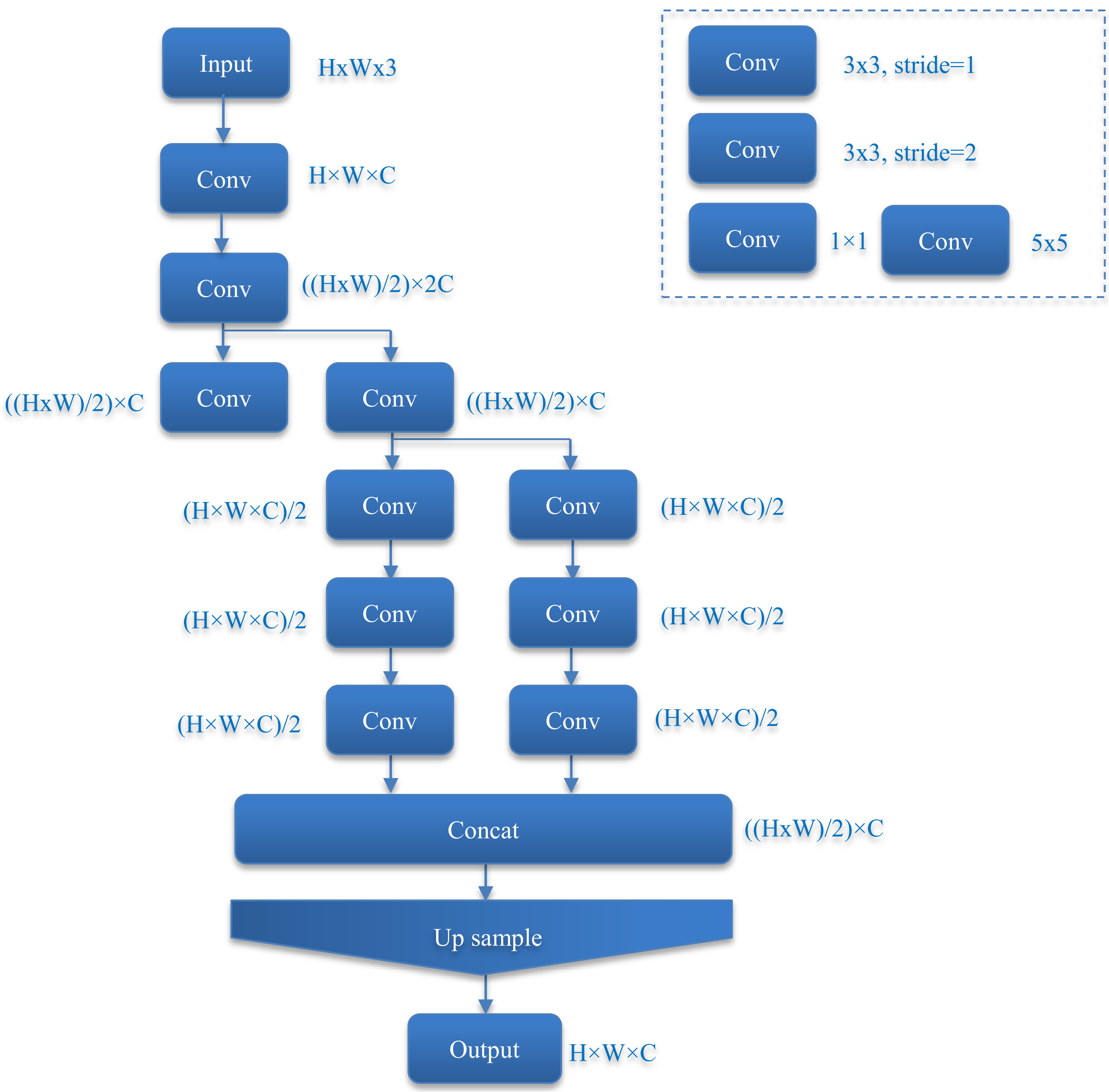


Fig. 3 Proposed MLAN

The object (trash) size in an image is not fixed and is highly dependent on the distance of the camera, so further multi-scale feature extraction layers are proposed. The previous layer output with output channels 2C divided the channels into two halves, where the first half of the information remained as it was. However, the other C channels are further divided into two C/2 channels, where the first half is passed through two 3×3 Conv layers and extracts features of a wider receptive field equivalent to 5×5, and the other half is passed through one 3×3 and one 5×5 to extend the receptive field wider, equivalent to 9×9.

These multi-scale features are then concatenated to obtain richer feature maps that capture both the local and global context. After concatenation, an upsampling layer is added to restore the spatial dimensions of the feature maps, allowing the model to recover lost spatial information. It is specifically beneficial for the task of classification.

3.4. Proposed Custom Bidirectional GRU

The design of the custom BiGRU, as shown in Figure 4, has been notably adapted to tackle the waste classification problem, where the aim is to accurately identify garbage based on sequential data patterns. The input layer is set to accept data representing a 128x128 grid with a single channel, which is commonly used for waste image data. The model consists of three BiGRU layers, each with eight GRU units, which allow it to grasp temporal relationships in the sequential nature of waste data. The bidirectional feature guarantees that the model takes into account information from both previous and future sequences simultaneously, improving its contextual comprehension.

Permute layers are carefully positioned to rearrange dimensions in the input data to ensure compatibility with the GRU layers. Each BiGRU layer undergoes Batch Normalization (BN) to stabilize training and enhance convergence. Let α and β be the learnable parameters, then after applying the BN on the output of BiGRU (y_i) given in Equation (9), it is as follows:

$$BN(y_i) = \alpha . \frac{y_i - \mu}{\sqrt{\sigma^2 + \epsilon}} + \beta \tag{9}$$

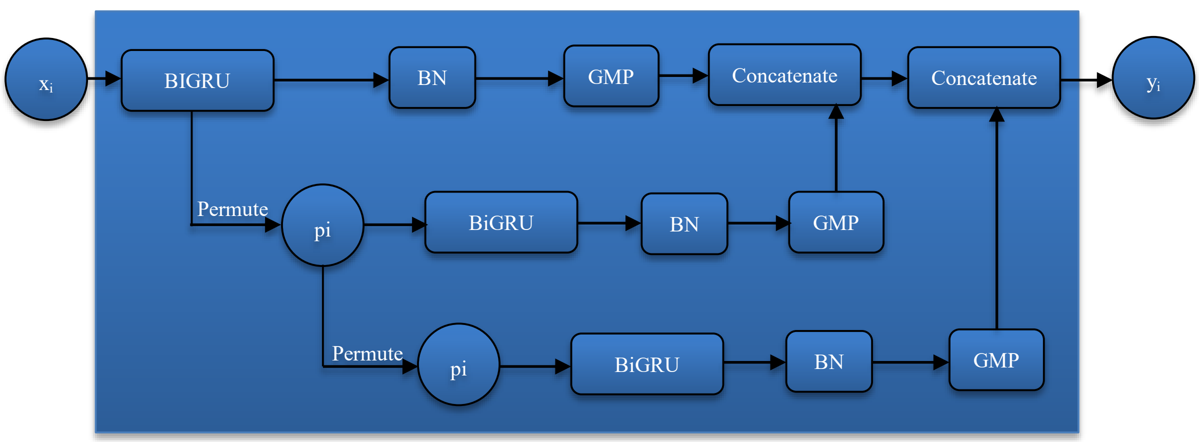


Fig. 4 Schematic diagram of proposed custom BiGRU

Here, μ is the mean, σ is the standard deviation, and ϵ is a small constant. After BN, Global Max Pooling (GMP) layers extract key characteristics from the sequential input, given as follows:

$$GMP\big(BN(y_i)\big) = max\big(BN(y_i)\big) \tag{10}$$

The characteristics generated from different layers are subsequently concatenated along the sequence axis, as shown in Figure 4, thus bringing together the context recorded by each BiGRU layer.

3.5. Proposed EBiGRU

The proposed EBiGRU architecture, specifically for waste classification, is able to detect complicated patterns and correlations in waste image sequences and classify them into biodegradable and non-biodegradable waste. The proposed architecture first extracts the multi-scale features using a novel MLAN backbone, which is then sequentially processed by a custom BiGRU.

It improves the feature representations by capturing local and global patterns and enhances the sequential dependencies. In this way, a model can handle objects at different scales, enhance contextual awareness, improve long-range dependencies and give smooth transitions across different scales.

This proposed architecture extracts the relevant information from the images and improves the system's capabilities. A dense layer at the end classifies the waste using learned features, as shown in figure 5.

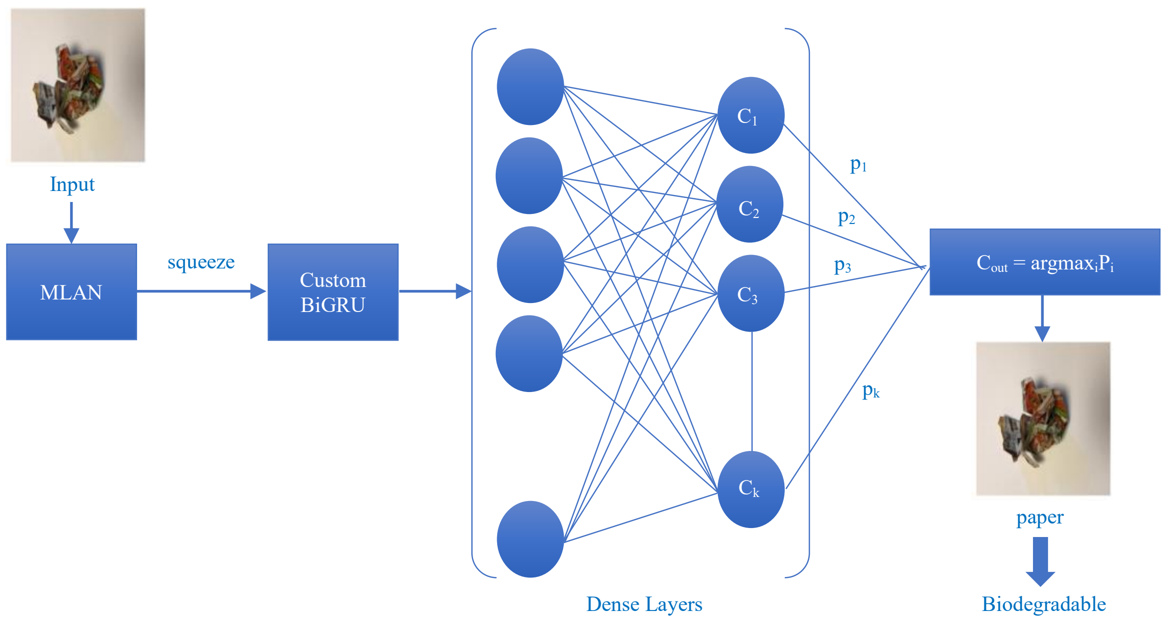


Fig. 5 Proposed EBiGRU architecture for waste classification

4. Experimentation and Result Analysis

The experiment section discusses different aspects of implementation, including dataset details, experimentation parameters, etc., for the problem of waste classification using proposed and other existing methods. The performance in terms of different performance metrics describes the model's effectiveness and provides an understanding of the proposed model architecture.

4.1. Dataset Details

The dataset used in this work is an image-based dataset that consists of different types of waste images. Two publicly available datasets, including the Waste Segregation Image dataset (Dutt & Dutt, 2023) and Garbage Classification (Chang, 2018), are used to evaluate the proposed model. Additionally, by combining these two datasets, a third dataset is generated that contains a greater number of classes for waste type. The details of all three datasets are discussed in this section, and sample images are shown in Figure 6.

4.1.1. Dataset 1

This dataset includes eight different types of waste images, such as paper, plastic bottles, bags, e-waste, metal cans, leaves, wood trash, and food. In total, this dataset has 14178 image samples for all these classes. Notably, the dataset systematically categorizes these classifications into the broader categories of biodegradable and non-biodegradable trash, which is an important difference in waste separation. It is worth noting that all images in this dataset vary in size and dimensions. However, these differences have been shown to have no discernible effect on the dataset's overall performance. This flexibility demonstrates the dataset's resilience since it can handle a wide range of image properties without impacting the models' performance in subsequent investigations.

4.1.2. Dataset 2

This dataset covers a wide range of waste categories, including glass, cardboard, metal, paper, plastic, and trash. To allow for a more thorough study, the garbage is divided into two categories: biodegradable and non-biodegradable, depending on the underlying character of each waste kind. It is worth mentioning that while glass does not technically fall into the conventional categories, it is included in the biodegradable group. This inference derives from the fact that, while glass is not biodegradable in the traditional sense, it has unique recyclability properties that make it environmentally sustainable. As a result, for this assignment, glass has been classified as biodegradable to recognize its potential for recycling and reuse, contributing to a more complete and environmentally responsible waste categorization strategy.

4.1.3. Dataset 3

The third dataset is a synthesis of the two previous datasets, seamlessly combining data points to generate a richer and more diversified collection. Certain classifications were consolidated as a result of this combination, yielding a dataset containing a total of ten distinct classes. These classes, in turn, have been carefully classified into the broader categories of biodegradable and non-biodegradable trash with the overarching goal of improving waste categorization. This combined dataset not only inherits the variety of the separate datasets but also adds a new dimension by combining related classes. This strategic combination intends to increase the dataset's resilience by providing a more holistic representation of waste categories for thorough analysis and classification activities.

Fig. 6 Sample images

4.2. Experimentation Setup

The evaluation of the proposed architecture takes place on a Windows-based system that uses its GPU capabilities to speed up computing procedures. The other system specifications are given in Table 1. The implementation takes advantage of the Python platform's adaptability and extensive ecosystem.

To meet the models' varying demands, multiple Python libraries are carefully installed under the precise requirements of each model's architecture. In total, 70% of the data is used for training for both GRU and EBiGRU architecture and the rest is used for testing purposes. All the training parameters for these architectures are given in Table 2, which has been decided based on experimentation.

Table 1. System specifications

Hardware	Specifications
Computer	Integrated GPU
CPU	Intel Core i7
RAM	16 GB
GPU	iRISx^{e} (8 GB)

Table 2. Training parameters

Training Parameter	Value
Epochs	100, 200
Optimizer	Adam
Loss Function	binary cross-entropy
Learning Rate	0.001

4.3. Results and Discussion

Different performance metrics such as accuracy, Correct Classification Rate (CCR), and loss are used to evaluate the performance of the proposed models. The accuracy offers a broad picture of a model's performance; it may not be the most appropriate statistic for unbalanced datasets. It is defined by the ratio of true vs. false predictions. Another performance metric, CCR, is defined as the percentage of accurately anticipated instances throughout the test dataset. It offers information on how successfully the model identifies and assigns the right class labels. It is very effective for dealing with datasets having skewed class distributions. Loss during training defines the difference between actual and predicted predictions. Based on these, the results are shown in Table 3, which are computed by setting up the same training environment for both GRU and EBiGRU models.

Table 3. Performance of GRU and EBiGRU on different datasets

Models	Accuracy			Loss		
	Dataset-1	Dataset-2	Dataset-3	Dataset-1	Dataset-2	Dataset-3
GRU (100 epochs)	85.39	57.66	73.01	0.4573	1.1001	0.7945
GRU (200 epochs)	83.32	68.5	78.47	0.5263	0.8201	0.6426
EBiGRU (100 epochs)	97.56	73.15	82.27	0.0753	0.0823	0.0918
EBiGRU (200 epochs)	**98.13**	**78.10**	**84.29**	**0.0611**	**0.0619**	**0.0884**

Figure 7 presents that on Dataset-1, the EBiGRU outperformed the GRU, with accuracies of 97.56% and 98.13% at 100 and 200 epochs, respectively. Moving on to Dataset 2, the EBiGRU maintained its lead, attaining an accuracy of 78.10% at 200 epochs, outperforming the GRU's best accuracy of 68.5% at the same epoch. In Dataset-3, the EBiGRU consistently beat the GRU in both epochs, with accuracy scores of 82.27% (100 epochs) and 84.29% (200 epochs). These findings demonstrate the EBiGRU's constant performance advantage over the GRU across a variety of datasets and epochs.

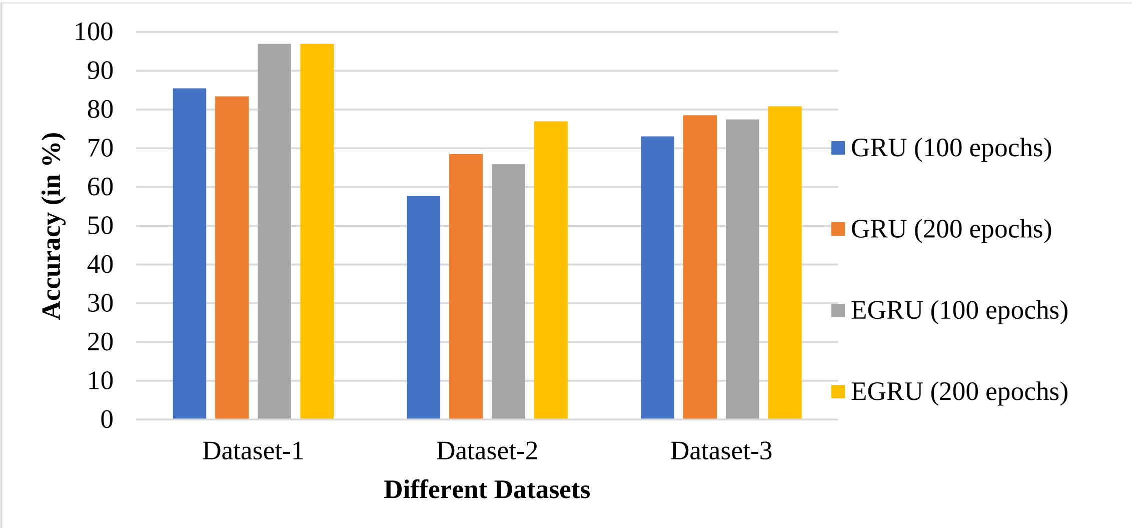


Fig. 7 Accuracy Comparison of different datasets

Similarly, on Dataset-1, the EBiGRU had the lowest loss values, at 0.0753 (100 epochs) and 0.0611 (200 epochs).

These results were far superior to the GRU's matching loss values. Continuing on to Dataset-2, the EBiGRU maintained to outperform the GRU, reaching loss values of 0.0823 (100 epochs) and 0.0619 (200 epochs), respectively. In Dataset-3, reflecting the accuracy trend, the EBiGRU recorded lower loss values, 0.0918 (100 epochs) and 0.0884 (200 epochs), compared to the GRU, shown in Figure 8. These results highlight the EBiGRU's persistent advantage over the GRU in minimizing loss across datasets and epochs.

Further, the performance metric CCR also analyses the performance of both GRU and EBiGRU on each dataset, which is given in Table 4.

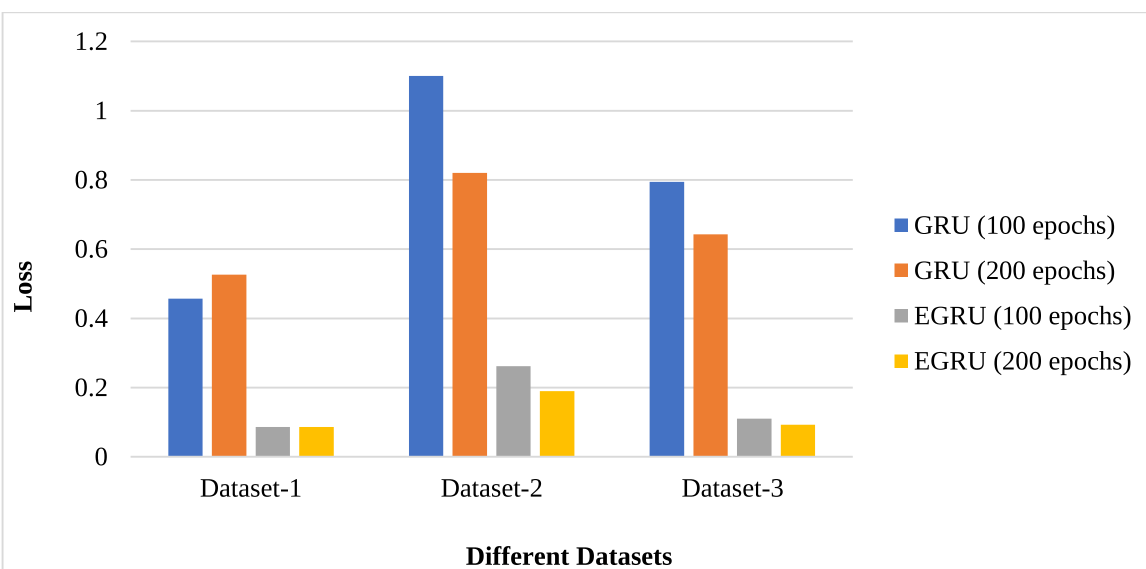


Fig. 8 Loss comparison of different datasets

Table 4. Correct classification rate

Models	CCR		
	Dataset-1	**Dataset-2**	**Dataset-3**
GRU (100 epochs)	42.46	53.34	74.37
GRU (200 epochs)	36.48	38.31	77.59
EBiGRU (100 epochs)	69.53	68.45	79.52
EBiGRU (200 epochs)	73.18	72.76	83.06

The comparison analysis is shown in Figure 9:

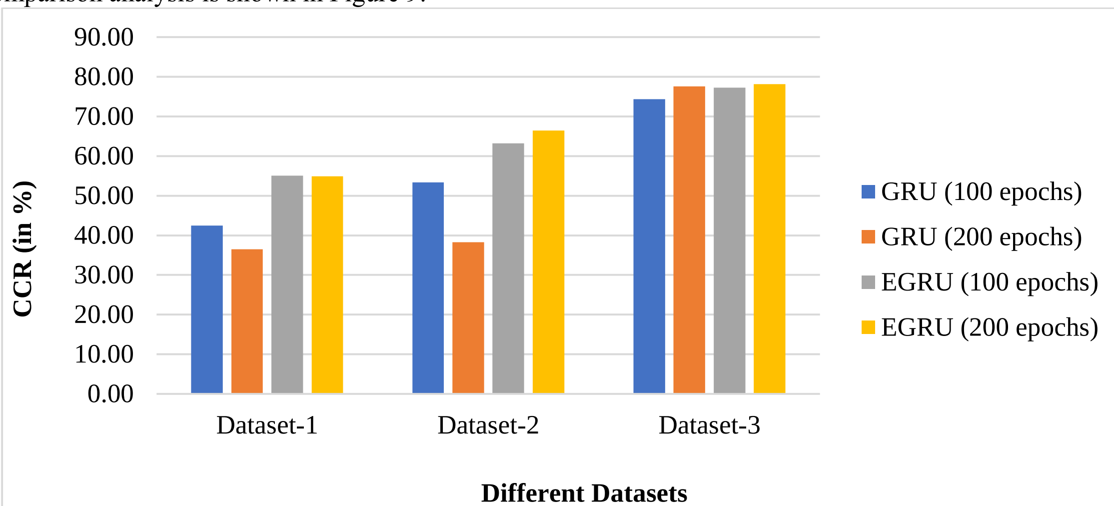
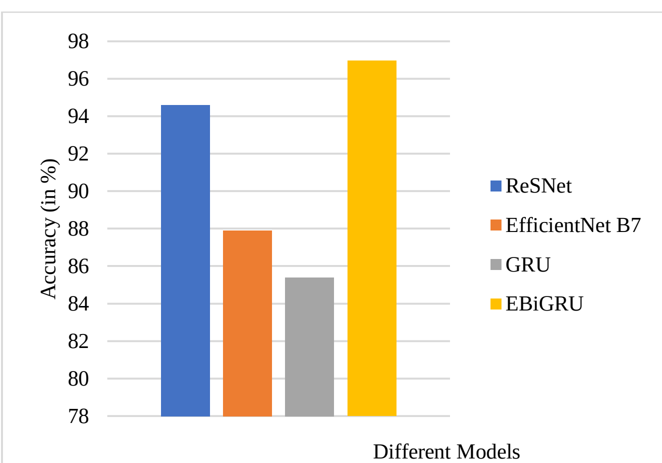


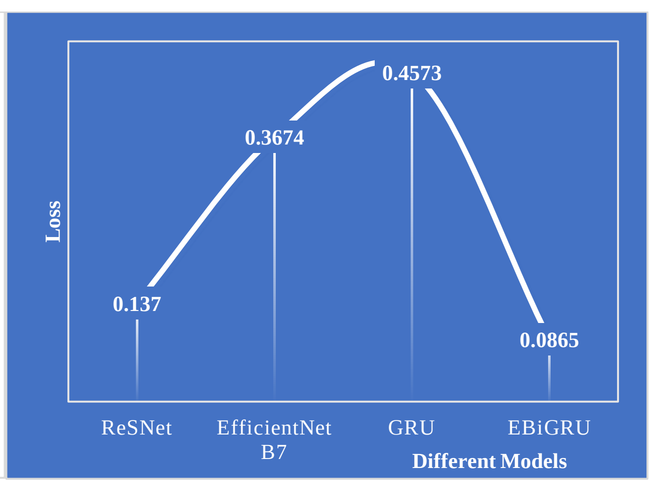
Fig. 9 CCR comparison of different datasets

This analysis reveals that with 100 epochs on Dataset-1, EBiGRU beats GRU, earning a CCR of 69.53% vs GRU's 42.46%. For Dataset-2, EBiGRU once again outperformed GRU with a CCR of 68.45%. On Dataset-3, EBiGRU again achieved a better CCR of 79.52%, whereas GRU had a lower CCR of 74.37%. After 200 epochs, EBiGRU maintained its performance on Dataset-1 with a CCR of 73.18%, whereas GRU's CCR fell to 36.48%. Dataset-2 showed that EBiGRU improved, with a CCR of 72.76%, which was higher than GRU's 38.31% percent. For Dataset 3, EBiGRU maintained its consistent performance with a higher CCR of 83.06%, while GRU's CCR is 77.59%.

4.4. Comparative Analysis

In the performance comparison study findings, the suggested EBiGRU's efficiency is compared to well-established models, specifically ResNet and EfficientNet B7. The comparison is based on the performance metric accuracy and loss, and is done using dataset 1 only.





(a) **(b)**

Fig. 10 Comparative analysis (a) Accuracy, and (b) Loss.

The results in Figure 10 present the effectiveness of the proposed EBiGRU based on its better performance in terms of high accuracy and lower loss compared to the other existing architectures. These results indicate the importance of the proposed method in this particular problem domain.

Also, the comparison with other state-of-the-art (SOTA) methods is presented in Figure 11, which presents the highest accuracy (98.13%) of the proposed architecture.

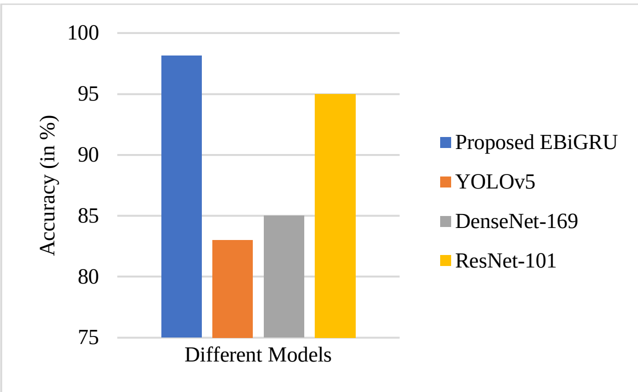


Fig. 11 Comparative analysis with SOTA

5. Conclusion

This research work aimed to develop an automatic waste classification technology using deep learning architectures. With this objective, CNN and RNN architectures were integrated into an EBiGRU architecture. This system is designed to be vision-based and uses only images for processing. The process starts with the extraction of multi-scale features using the proposed MLAN architecture from the images. Then it passes these features to the customized BiGRU architecture, naming it EBiGRU.

The proposed architecture is evaluated on three different datasets with different classes of waste materials, with the same training and test parameters. The results in terms of accuracy, loss, and CCR presented in different graphs have shown the effectiveness of the proposed architecture. The comparison with other SOTA methods also shows the significant benefits of the proposed method. Further, the classified waste is categorized into biodegradable and non-biodegradable waste. In the future, the proposed method needs to be evaluated on a real-time setup and embedded in a hardware unit to create an automated robotic system for waste segregation.

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