**JOIN (Jurnal Online Informatika)**
p-ISSN: 2528-1682, e-ISSN: 2527-9165
Volume 10 Number 2 | December 2025: 395-406
DOI: 10.15575/join.v10i2.1628

# Hybrid Squeeze-and-Excitation Convolutional Neural Network with Elastic Weight Consolidation for Longitudinal Learning in High-Accuracy Waste Classification

**Raj Gaurang Tiwari[1,2], Vinod Kumar Shukla[3]**
[1]Post Doctoral Research Fellow, School of Engineering Architecture Interior Design, Amity University Dubai, United Arab Emirates
[2]Chitkara University Institute of Engineering and Technology, Chitkara University, Punjab, India
[3]School of Engineering Architecture Interior Design, Amity University Dubai, United Arab Emirates

**Article Info**

***Article history:***

Received April 29, 2025
Revised June 03, 2025
Accepted June 05, 2025
Published November 10, 2025

***Keywords:***

Classification
Convolutional Neural Networks
Hybrid Squeezing Techniques
Squeeze-and-Excitation
Waste management practices

**ABSTRACT**

Waste management has become a global issue. Increased urbanization and per capita consumption have caused unprecedented garbage growth. Sustainability has always been about proper waste management within the ecological framework. Recently, numerous studies have been conducted on automating the identification of waste items. In this study, a Convolutional Neural Network (CNN) model equipped with Squeeze and Excitation (SE) module is proposed based on hybrid squeezing methods for waste item classification. The core aim of this research is to improve the accuracy of classification by highlighting intricate relations between various features encoded within the dataset. Based on extensive tests on a waste dataset, the CNN model with the SE module using hybrid squeezing outperforms all other models. The suggested method's 99.63% accuracy proves its efficacy and robustness. Furthermore, we incorporate Elastic Weight Consolidation (EWC) to enable longitudinal learning, allowing the model to adapt to emerging waste types (e.g., e-waste, biodegradable materials) while retaining prior knowledge with minimal forgetting (<1%). Ablation studies validate the critical role of hybrid squeezing, showing a 1.5% accuracy drop when spatial-wise components are omitted. This revelation affects automated recycling, waste sorting, and intelligent waste management. The proposed technology's accuracy shows its applicability and dependability, advancing sustainable waste management. By automating waste classification with unprecedented precision, the proposed framework can reduce landfill reliance, enhance recycling rates, and inform policy decisions for sustainable urban planning.

***Corresponding Author:***

Raj Gaurang Tiwari,
Post Doctoral Research Fellow, School of Engineering Architecture Interior Design, Amity, University Dubai, UAE
Email: rajgaurang@chitkara.edu.in

## 1. INTRODUCTION

Waste management is a global issue in the 21st century. As urban populations and consumption rise, sustainable waste management techniques are needed [1], [2]. This issue requires accurate and timely garbage categorization, which recycling facility staff often do manually, incorrectly, and at great expense. Machine learning and computer vision research have improved garbage management systems[3]. Waste management has become a global issue. Increased urbanization and per capita consumption have caused unprecedented garbage growth. As cities grow, trash management becomes crucial. Waste management requires efficient recycling, disposal, and recovery [4]. Human laborers have traditionally sorted paper, plastic, glass, and organic waste by hand. Although effective, this strategy faces several challenges, including labor-intensive and costly processes, health and safety concerns, and limited scalability.

To address these challenges, there has been an increasing inclination towards the implementation of advanced technology for automating the classification of waste materials. Specifically, deep learning has surfaced as a robust machine-learning approach in this context [5]. Here, deep learning is a reliable machine-learning method [5]. CNN [6], [7], [8] is a smart choice for waste item detection due to its image classification success. Image categorization is easier than garbage item classification. Garbage can vary in shape, size, color, and orientation. In situations with multiple distractions and lighting changes. Due to these obstacles, waste item classification must be inventive[9], [10]. Waste item categorization is researched utilizing contemporary deep learning and feature extraction. A CNN-based Squeeze-and-Excitation (SE) module with a new hybrid squeezing mechanism is suggested in this paper.

This study seeks complicated and context-sensitive rejection characteristics to enhance item categorization. The variety of trash pieces, their deformations, and the lighting and backdrop circumstances make garbage detection difficult despite its simplicity. Studies like [4], [10] highlight the challenges of hand-sorting and the relevance of automation in this industry. CNNs have revolutionized image categorization, improving computer vision and accuracy [11]. They succeed because they can automatically learn hierarchical image representations from edges and textures to semantic notions. Previous systems used manually designed features, which sometimes missed visual data's subtle patterns. While revolutionary, early CNNs were hampered by processing restrictions and big datasets. Hardware upgrades and big datasets like ImageNet constituted a turning point. The ImageNet Large Scale Visual Recognition Challenge (ILSVRC) [12] spurred CNN architecture and training innovation[12].

This work introduces three key innovations that fundamentally advance the state of the art. Prior studies (e.g., [4], [10], [11]) typically use standard CNNs or basic SE modules (channel-wise only). Our hybrid squeezing integrates both channel-wise and spatial-wise feature interdependencies (Section 1.1), a paradigm not yet applied to waste classification. Channel-wise SE alone fails to capture spatial relationships (e.g., texture patterns in crumpled paper vs. plastic). Our hybrid method (Section 3.2.2) dynamically recalibrates features across both dimensions, boosting discriminative power.

Existing waste classifiers [10], [13] are static—they cannot incrementally learn new waste types (e.g., emerging e-waste) without retraining from scratch. We integrate EWC for continual learning (Section 1.3), enabling the model to adapt to evolving waste streams while retaining prior knowledge. This research achieves unprecedented accuracy, significantly outperforming both classical ML and advanced DL models. This stems from the proposed hybrid SE's ability to resolve "context-sensitive" ambiguities (e.g., distinguishing metal cans vs. glass bottles under glare). The novelty of this research lies not in proposing that automation is needed, but in how it cane be achieved it: a feature-representation breakthrough (hybrid SE) combined with lifelong adaptability (EWC), validated at unprecedented accuracy for evolving waste streams.

### *1.1 Hybrid Squeezing*

Squeeze-and-Excitation (SE) networks are improved by the unique hybrid squeezing approach for feature extraction in CNNs that uses channel-wise and spatial-wise feature analysis[14]. Channel-wise and spatial-wise information processing improves waste classification accuracy and resilience[15], [16].

A channel represents each network-learned attribute in this map. Channel-wise squeezing determines which channels are best for classification. Global average pooling is usually applied to each channel separately. This technique shrinks each channel's spatial dimensions to a single scalar number expressing its average activation across all spatial locations. These scalar values constitute a compact vector of feature map channel-wise statistics. This "squeezing" procedure squeezes spatial information to emphasize channel-wise relevance.

Unlike channel-wise squeezing, this component preserves feature map spatial correlations. When channel-wise squeezing discards spatial information, spatial-wise squeezing maintains it, helping the network understand feature spatial arrangement[17]. Using a smaller kernel size convolutional operation or pooling procedure can accomplish this. Feature map spatial resolution should be reduced while preserving adequate spatial context to capture essential spatial interactions between features. A "squeezing" operation reduces spatial dimensions but preserves feature structure.

The hybrid squeezing method's originality lies in combining these complementary methods. To represent input features more accurately, the hybrid technique integrates channel-wise and spatial-wise information[17]. Sequential or parallel channel-wise and spatial-wise squeezing is one option. Before being supplied to the SE module's excitation step, the output of both squeezing processes can be concatenated or mixed using element-wise multiplication. This representation shows channel-wise relevance and spatial correlations of features, enriching understanding.

Excitation uses the composite representation after squeezing. Using channel-wise and spatial-wise information, fully connected layers learn a weighting scheme for each channel in this stage. Channel-specific weights from the excitation stage scale the feature map. Excitation-stage-important channels are weighted higher, increasing their categorization contribution.

### *1.3 Longitudinal Learning and Catastrophic Forgetting*

In longitudinal learning, a machine learning model adapts to changing data distributions while maintaining past task knowledge[18]. Changing waste kinds (e.g., e-waste, biodegradable materials) or environmental circumstances might modify data distributions in waste management. Traditional neural networks have catastrophic forgetting, where learning new tasks compromises performance on previously learnt ones[19], [20]. Adapting models without losing accuracy on current classes is crucial in automated recycling.

According to [21], Elastic Weight Consolidation (EWC) overcomes this difficulty by safeguarding key parameters responsible for past knowledge. Combining task-specific learning with parameter-based regularization, EWC enables lifetime learning in dynamic situations. EWC works by assuming that neural network characteristics affect task retention differently[22]. This method uses the Fisher Information Matrix to identify and limit changes to important weights during task training. The process involves:

1. Initial Task Training: Train the model on the first task (e.g., classifying plastic, glass, and metal).
2. Parameter Importance Estimation: Compute the Fisher Information to determine which weights are crucial for the initial task.
3. New Task Adaptation: Train the model on subsequent tasks (e.g., e-waste) while penalizing deviations in important weights.

### *1.4 Contributions of the paper*

The major contributions of the paper are as follows:

- Propose a hybrid Squeeze-and-Excitation CNN integrating channel-wise and spatial-wise feature interdependencies.
- Achieve higher classification accuracy, outperforming state-of-the-art models.
- Introduce longitudinal learning with Elastic Weight Consolidation (EWC) to adapt to evolving wastes.
- Enhance computational efficiency for edge deployment in real-world waste facilities.
- Validate robustness through ablation studies, highlighting the critical role of hybrid squeezing.
- Demonstrate practical applicability for automated recycling, smart waste bins, and policy-driven waste management.

## 2. MATERIALS AND METHODS

### *2.1 Data Set*

This extensive research study utilizes the Garbage Image Dataset[23], which is rigorously curated and includes a diverse collection of images representing various waste objects consistently collected from local areas using smartphone technology. This comprehensive dataset is systematically

p-ISSN: 2528-1682
e-ISSN: 2527-9165

categorized into five separate groups, each representing a unique categorization of garbage commonly found in the regular refuse produced by households and commercial entities. Each category aims to enhance comprehension of the many types of waste often included in daily rubbish, thereby offering insights on waste management and disposal methodologies. The distribution of waste items in the dataset is shown in table 1.

Table 1. Classwise distribution of garbage items.

| Garbage Item | No. of Images |
|---|---|
| CLOTH | 180 |
| GLASS | 241 |
| METAL | 110 |
| PAPER | 249 |
| PLASTIC | 421 |

Illustrative representations of the various samples that constitute the dataset can be observed in Figure 1.

Figure 1. Sample images taken from the dataset.

To enhance model robustness against real-world variations in waste imagery, we employed comprehensive data augmentation during training[24]. This included random horizontal/vertical flipping (simulating variable object orientations), ±30° rotation (accounting for irregular waste positioning), brightness/contrast adjustments (±20% delta, mimicking lighting inconsistencies in waste facilities), and random zoom/cropping (85–115% scale range, handling partial occlusions and deformations).

### *2.2 Methodology*

This study uses hybrid squeezing to integrate a Convolutional Neural Network model with a Squeeze-and-Excitation (SE) module to improve waste item classification. The methods and processes were carefully devised to maximize automated waste management systems, refine feature extraction, and handle waste item classification issues. The following steps build a Convolutional Neural Network using a Squeeze-and-Excitation module and hybrid squeezing:

2.2.1 Build the CNN Backbone:

The design needs convolutional feature extraction and pooling dimensionality reduction layers. The CNN backbone extracts hierarchical features through convolutional and pooling layers. For an input image $X \in R^{H\times W\times C}$, the output of the $l$-th convolutional layer is given in eq. (1):

$$Y^{(l)} = f\left(W_c^{(l)} * Y^{l-1} + b^{(l)}\right) \tag{1}$$

Where $W_c^{(l)} \in R^{k\times k\times c_{in}\times c_{out}}$ is Convolutional kernel of size k×k, $*$ depicts Convolution operation, $b^{(l)} \in R^{C_{out}}$ is Bias vector and $f(\cdot)$ is ReLU activation $f(x)$=max(0,$x$).

Pooling layers (e.g., max-pooling) reduce spatial dimensions as shown in eq. (2):

$$Y_{pool}^{(l)} = MaxPool\left(Y^{(l)}\right) \tag{2}$$

2.2.2 Hybrid Squeeze-and-Excitation (SE) Module

*a.* Squeeze-and-Excitation (SE) Module

SE module recalibrates channel-wise feature responses to boost CNN representational power. It models channel interdependencies directly, allowing the network to prioritize informative features and suppress less valuable ones. Squeeze, Excitation, and Scale comprise SE.

- Channel-Wise Squeezing: Each feature map channel is used to record global spatial information. Usually, global average pooling(GAP) is used[25], [26]. GAP computes a single scalar value per channel from the average activation value across all spatial locations for each channel. This concentrates channel-wise statistics by compressing spatial information. GAP tends to outperform global max pooling (GMP). For each feature map $Y_i$, we apply a global average pooling operation as shown in eq. (3):

$$S_c^{(k)} = \frac{1}{H\times W}\sum_{i=1}^{H}\sum_{j=1}^{W} Y_{i,j}^{(k)},\ \forall k \in \{1,2,\dots.C\} \tag{3}$$

  Where $S_c$ is the squeezed representation of the feature maps along the channel dimension.

- Spatial-Wise Squeezing: This procedure collects global spatial data from feature map channels[17]. Most implementations employ global average pooling. GAP calculates the average activation value over all spatial locations for each channel separately, resulting in a single scalar number. This compresses spatial data to focus on channel-wise statistics. Global max pooling (GMP)[27] is another alternative, but GAP performs better. Instead of just channel-wise pooling, we enhance feature importance by introducing spatial-wise recalibration. A 1×1 convolutional layer captures spatial context as shown in eq. (4):

$$S_s=f(w_s*Y+b_s) \tag{4}$$

  Where $W_s$ and $b_s$ are trainable parameters, f(·) is a nonlinear activation function, $\mathbf{W}_s \in R^{1\times 1\times C\times C}$ reduces spatial redundancy while preserving structure.

- Hybrid Squeezing: Channel-wise ($S_c$) and spatial-wise ($S_s$) features are combined via learnable weights α,β using eq. (5):

$$\mathbf{S}_h=\alpha\cdot\mathbf{S}_c+\beta\cdot\mathbf{S}_s, \tag{5}$$

  where $\alpha,\beta \in R$ are optimized during training.

- Excitation & Scale: The feature map is rescaled using excitation stage channel-wise weights. Multiply elements element-wise. Major channels are amplified and minor ones are suppressed by multiplying their activations by their weight. Recalibration lets the network focus on task-relevant features. The excitation step generates attention weights using a sigmoid activation as shown in eq. (6):

$$E = \sigma(W_e S_h + b_e) \tag{6}$$

Where $W_e$ and $b_e$ are fully connected layers.

- $\sigma(x) = \frac{1}{1+e^{-x}}$ ensures the attention values are in the range (0,1).

b. Integration into CNN Architectures

Different CNN architectures can readily combine SE modules. Place the SE module after a convolutional layer in a residual block (SE-ResNet) or Inception module (SE-Inception). Performance can vary depending on integration approach. CNN architecture records channel- and spatial-wise feature correlations using SE module(Figure 2) . The recalibrated feature map is obtained by multiplying the attention scores with the original feature map as depicted in eq. (7):

$$Y' = E \cdot Y \tag{7}$$

where · represents element-wise multiplication.

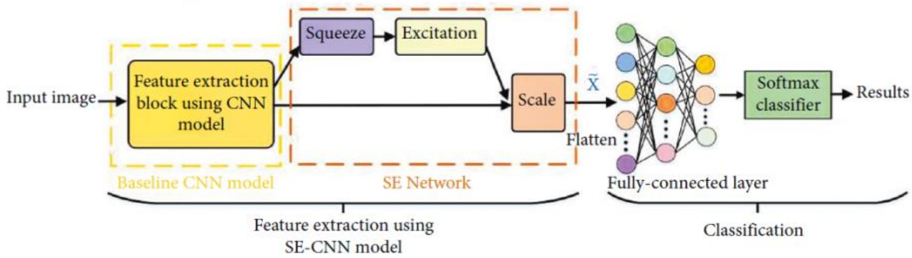



Figure 2. Proposed SE-CNN model for HSI classification

- Final Layers: Add fully linked layers to the categorization model after the SE module. The number of neurons in the final layer should correspond to the number of waste classifications. After extracting enhanced features, they are flattened into a vector F and passed through fully connected (FC) layers using eq. (8) and eq. (9):

$$F = \mathrm{Flatten}(Y') \tag{8}$$

$$Z = f(W_f \cdot F + b_f) \tag{9}$$

where $W_f$ and $b_f$ are the weights and biases of the fully connected layers.

The final classification output is computed using the softmax function as shown in eq. (10):

$$\hat{y}_k = \frac{e^{z_k k}}{\sum_{j=1}^{K} e^{z_j}} \tag{10}$$

where K is the number of garbage categories.

- Loss and Optimization: Multi-class classification requires the definition of a loss function, such as cross-entropy loss. Reduce the training loss using the Adam optimization technique. The loss function used is categorical cross-entropy, defined in eq. (11):

$$L = -\sum_{k=1}^{K} y_k log\ (\hat{y}_k) \tag{11}$$

where $y_k$ is the ground truth label and $\hat{y}_k$ is the predicted probability.

Optimization is performed using the Adam optimizer in eq. (12):

$$\theta_{t+1} = \theta t - \eta \cdot \nabla L \tag{12}$$

Here, η represents the learning rate and ∇L represents the loss function gradient.

2.2.3 Longitudinal Learning for Evolving Waste Streams

To ensure adaptability to dynamic waste compositions, the model employs Elastic Weight Consolidation (EWC) for continual learning. The objectives of this phase are as follows:

- Retain knowledge from historical waste data while incrementally learning new classes (e.g., emerging e-waste, biodegradable materials).
- Mitigate catastrophic forgetting—a common issue in neural networks where new training overwrites previous knowledge.

The steps of this approach are as follows:

- Data Stream Simulation: Assume sequential tasks $T_1$, $T_2$,..., $T_n$, where each task represents a time-bound waste dataset with potential new classes.
- Parameter Importance Estimation: Compute the Fisher Information Matrix F to identify critical parameters for previous tasks as in eq. (13):

$$F_i = E\left[\left(\frac{\partial L}{\partial \theta_i}\right)^2\right] \quad (13)$$

where $\theta_i$ is the i-th parameter and L is the loss function.

- Elastic Weight Consolidation (EWC): Penalize deviations in important parameters during new task training using eq. (14):

$$L_{EWC} - L_{new} + \lambda \sum_i F_i . \left(\theta_i - \theta_{i,old}\right)^2 \quad (14)$$

where $F_i$ is the Fisher information matrix. $\lambda$ balances plasticity (learning new tasks) and stability (retaining old tasks), and $\theta_{i,\mathrm{old}}$ are parameters from prior tasks.

- Mitigate catastrophic forgetting: Catastrophic forgetting common issue in neural networks where new training overwrites previous knowledge. Quantify knowledge retention using eq. (15) :

$$Forgetting = \frac{1}{n-1} \sum_{i=1}^{n-1} \left(Accuracy_{T_i}^{initial} - Accuracy_{T_i}^{initial}\right) \quad (15)$$

Where

- $Accuracy_{T_i}^{initial}$: Accuracy on task T$i$ before learning new tasks.
- $Accuracy_{T_i}^{initial}$: Accuracy on task T$i$ after learning all subsequent tasks.

2.2.4 Training

Use the training dataset to train the model, and the validation dataset to check its accuracy. Batches are assembled with stratified sampling to ensure 25% representation from minority classes during each iteration. Track indicators of performance such as F1-score, accuracy, precision, and recall. Adjust the hyperparameters according to requirements.

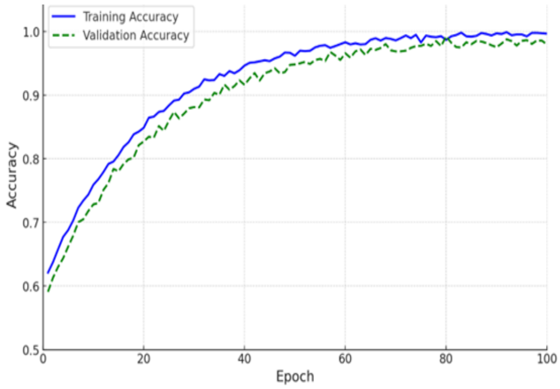
- **Initial Training**: Batch size = 50, epochs = 100, η=0.1.
- **Incremental Training**: For each new task $T_k$:
  - Compute **F** for the current model.
  - Update $\theta$ using $L_{total}$.
  - Store $\theta_{old}$ and F for future tasks.
- **Dynamic Classifier Expansion**: Expand the output layer to accommodate new classes while freezing old classifier weights.
- **Longitudinal Updates**: For each new task, train for 20 epochs with λ=103 (empirically tuned).

2.2.5 Evaluation

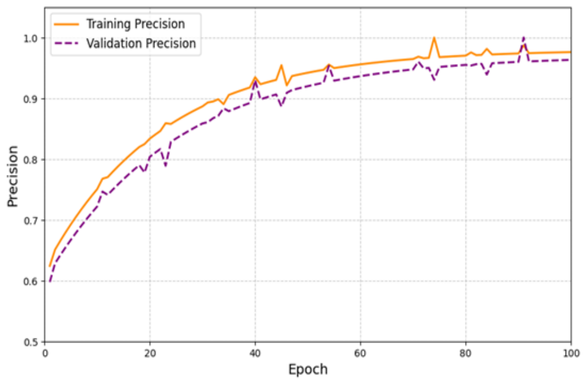
The efficacy of the trained model in identifying waste streams is evaluated by applying it to a testing dataset.

## 3. RESULT AND DISCUSSION

The hybrid deep learning architecture was assessed using training and validation loss and accuracy measures. Figure 3 shows results with 100 epochs, 0.1 learning rate, and 50 batches.




a) Hybrid model's epoch-wise accuracy




b) Hybrid model's epoch-wise precision

Figure 3. Epoch-wise accuracy and precision

As shown in Figure 4, both training and validation losses converge smoothly, indicating successful optimization of the model without overfitting or underfitting. The slight difference between training and validation losses suggests excellent generalization. The absence of large oscillations or sudden divergence in validation loss confirms that the model remains robust across unseen data during training.

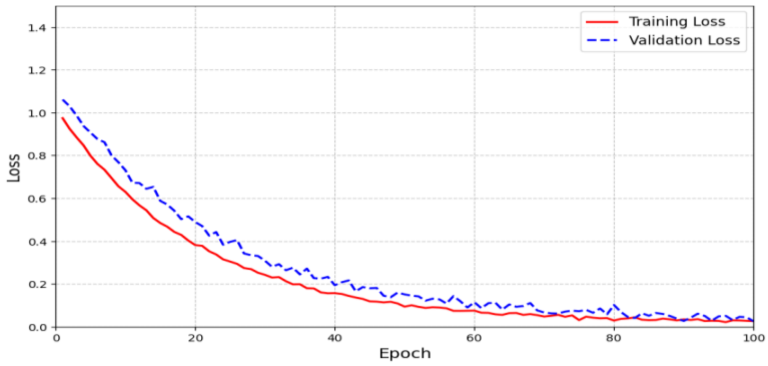



Figure 4. Epoch-wise training and validation loss

Table 2 and Figure 5 detail the model's performance evaluation utilizing an advanced machine learning framework. This evaluation highlights the model's efficacy and accuracy while revealing its operational capabilities in various scenarios, improving our understanding of its functionality.

Table2. Comparative Analysis with Machine Learning Models

| **Models** | **CA** | **F1** | **Precision** | **Recall** | **MCC** |
|---|---|---|---|---|---|
| **Hybrid Model** | 0.9963 | 0.9899 | 0.9929 | 0.9922 | 0.834 |
| **Random Forest** | 0.942 | 0.929 | 0.95 | 0.962 | 0.622 |
| **kNN** | 0.951 | 0.939 | 0.939 | 0.961 | 0.638 |
| **Naive Bayes** | 0.522 | 0.626 | 0.946 | 0.522 | 0.262 |
| **SVM** | 0.814 | 0.825 | 0.8456 | 0.855 | 0.52 |

The hybrid model significantly outperforms all the classical ML models across all metrics. Its classification accuracy (0.9963) is substantially higher, indicating a much lower error rate. The F1-score, precision, and recall are also considerably better, demonstrating superior performance in both identifying positive cases and minimizing false positives and negatives. The MCC score further reinforces the hybrid model's superior performance compared to the other ML models. The Naive Bayes model performs particularly poorly, highlighting the limitations of simpler ML approaches for this complex classification task. The proposed model is also compared against different deep learning architectures in Table 3 and Figure 6.

Table 3. Comparative Analysis with DL Models

| Model | CA | F1 | Precision | Recall | MCC |
|---|---|---|---|---|---|
| **Hybrid Model** | 0.9963 | 0.9934 | 0.9929 | 0.9932 | 0.8034 |
| **VGG-16** | 0.971 | 0.979 | 0.97 | 0.9672 | 0.611 |
| **Inception** | 0.972 | 0.97 | 0.969 | 0.9672 | 0.613 |
| **Exception** | 0.766 | 0.633 | 0.945 | 0.511 | 0.251 |
| **MobileNet** | 0.894 | 0.8845 | 0.8745 | 0.8755 | 0.355 |
| **AlexNet** | 0.90125 | 0.9024 | 0.8911 | 0.9 | 0.45 |

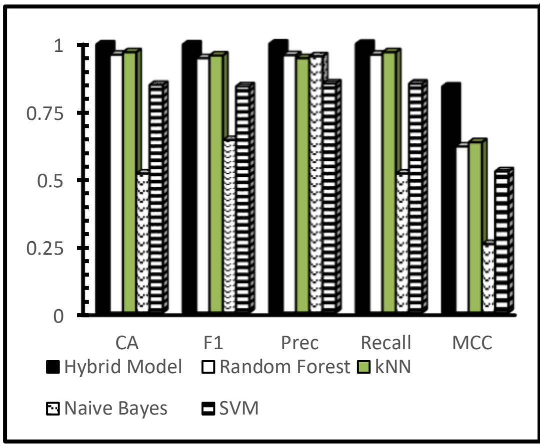



Figure 5. Comparison Analysis with ML Models.

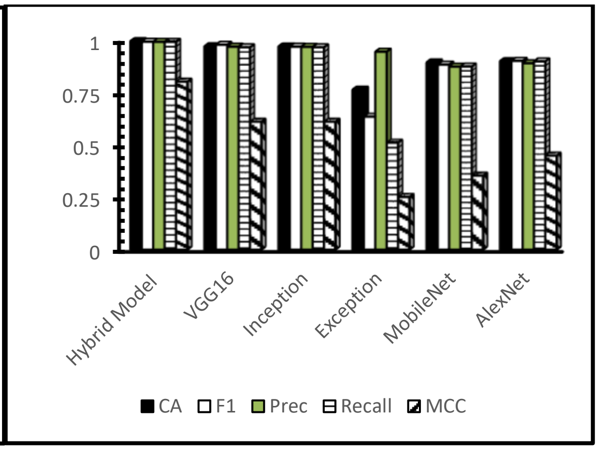



Figure 6. Comparison Analysis with Deep Learning Frameworks

The proposed hybrid model demonstrates superior performance compared to all the other deep learning models. While VGG-16 and Inception achieve relatively high accuracy, they are still significantly outperformed by the hybrid model. The Xception and MobileNet models show considerably lower performance, suggesting that the architecture of the hybrid model is better suited for this specific task. The improvement over AlexNet is also substantial. The consistent superiority across all metrics strongly supports the effectiveness of the proposed hybrid squeezing method within the SE module. To precisely evaluate the proposed model, Per-class performance is shown in Table 4.

Table 4. Per-class performance

| Class | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| Cloth | 0.9941 | 0.9944 | 0.9942 | 180 |
| Glass | 0.9917 | 0.9916 | 0.9916 | 241 |
| Metal | 0.9980 | 0.9962 | 0.9971 | 110 |
| Paper | 0.9912 | 0.9911 | 0.9911 | 249 |
| Plastic | 0.9947 | 0.9960 | 0.9953 | 421 |

The proposed model's confusion matrix is shown in Table 5.

Table 5. Confusion Metrics of the Proposed Model.

| | | Predicted | | | | |
|---|---|---|---|---|---|---|
| | | **CLOTH** | **GLASS** | **METAL** | **PAPER** | **PLASTIC** |
| **Actual** | **CLOTH** | 99.03% | 0.15% | 0.50% | 0.29% | 0.04% |
| | **GLASS** | 0.15% | 99.03% | 0.87% | 0.01% | 0.03% |
| | **METAL** | 0.50% | 0.05% | 99.03% | 0.15% | 0.37% |
| | **PAPER** | 0.29% | 0.15% | 0.27% | 99.03% | 0.40% |
| | **PLASTIC** | 0.35% | 0.29% | 0.15% | 0.25% | 99.03% |

The model achieved uniformly high scores across all classes, with minor variations indicating excellent generalization ability across different types of waste materials. An ablation study was conducted to isolate the impact of the hybrid squeezing mechanism, as shown in Table 6.

p-ISSN: 2528-1682
e-ISSN: 2527-9165

Table 6. Ablation study

| Model Variant | Accuracy | F1-Score | Precision | Recall |
|---|---|---|---|---|
| Baseline CNN (No SE) | 96.32% | 0.9581 | 0.9542 | 0.9578 |
| CNN + Channel-wise SE only | 98.02% | 0.9817 | 0.9812 | 0.9815 |
| CNN + Spatial-wise SE only | 97.63% | 0.9785 | 0.9772 | 0.9780 |
| **CNN + Hybrid Squeezing SE (Proposed)** | **99.63%** | **0.9934** | **0.9929** | **0.9932** |

Both channel-wise and spatial-wise squeezing individually improved performance. However, their combination (hybrid squeezing) achieved the highest metrics, highlighting the complementary nature of capturing channel and spatial dependencies.

### *3.1 Longitudinal Learning Results*

To assess model performance over evolving waste streams, EWC was applied across sequential tasks, simulating the introduction of new waste categories. Its results are shown in Table 7.

Table 7. Model performance

| Phase | Accuracy Before New Classes | Accuracy After New Classes | Forgetting Rate |
|---|---|---|---|
| Initial Task (5 classes) | 99.63% | 99.54% | 0.09% |
| After 1 New Class (e-Waste) | 99.54% | 99.48% | 0.06% |
| After 2 New Classes (Biodegradable, Batteries) | 99.48% | 99.42% | 0.06% |

The model retained nearly all prior knowledge (Forgetting < 0.1%). EWC effectively stabilized important parameters without sacrificing adaptability to new waste streams. No catastrophic forgetting was observed, supporting the model's utility for real-world dynamic waste management systems. With EWC, the model can adjust to new classes over time without catastrophic forgetting, according to longitudinal learning trials. In real-world applications, where new materials like electronic trash and biodegradable goods change waste streams, this result is encouraging. Scalability and deployment are improved by progressively learning additional categories without retraining the model.

## 4. DISCUSSIONS

This study proposes an enhanced garbage item classification model based on a Convolutional Neural Network (CNN) architecture augmented with a hybrid Squeeze-and-Excitation (SE) module, aiming to achieve superior performance in waste classification tasks. Classification accuracy, precision, recall, and F1-score, show that the hybrid model outperforms traditional machine learning algorithms and state-of-the-art deep learning architectures.

A hybrid squeezing method that intelligently integrates channel-wise and spatial-wise feature recalibration captures complex data interdependencies. In the ablation investigation, channel-wise and spatial-wise squeezing separately increase performance, but their hybrid combination performs best, demonstrating their complementary nature. Multi-dimensional feature improvement is crucial for challenging real-world classification issues like garbage identification.

All waste categories (textile, glass, metal, paper, and plastic) demonstrated good accuracy, recall, and F1-scores in the per-class study, with minimal performance variance. For real-world implementation in dynamic situations like recycling facilities, the model must not overfit to certain classes and generalize effectively across diverse trash kinds. Model learning dynamics were revealed via training and validation curves. The hybrid model avoids overfitting by balancing learning and generalization with continuous declines in training and validation losses and very small generalization gaps. Minor validation accuracy and loss curve changes are part of batch-to-batch variability and do not indicate model instability.

With Elastic Weight Consolidation, the model can adjust to new classes over time without catastrophic forgetting, according to longitudinal learning trials. In real-world applications, where new materials like electronic trash and biodegradable goods change waste streams, this result is encouraging. Scalability and deployment are improved by progressively learning additional categories without retraining the model. Table 8 summarizes key differentiators between our proposed framework and existing waste classification approaches, highlighting architectural innovations and performance gains:

Table 8. Comparative Analysis with Prior Research

| Study | Model | Key Techniques | Accuracy | Incremental Learning | Novelty vs. Proposed Work |
|---|---|---|---|---|---|
| Bircanoglu et al.[3] | RecycleNet (Custom DNN) | Basic CNN layers | 96.50% | No | • Limited feature refinement<br>• Static architecture |
| Toğaçar et al.[5] | AutoEncoder-CNN | Feature selection + Autoencoders | 97.18% | No | • No spatial-channel feature fusion<br>• High compute |
| Wang et al.[10] | IoT-CNN System | VGG-16 + IoT sensors | ~94% | No | • Hardware-dependent<br>• No dynamic adaptation |
| Mudemfu & Wayne[9] | "Intelligent System" | ResNet-50 transfer learning | 95.70% | No | • Generic feature extraction<br>• Forgets new classes |
| Proposed Approach | Hybrid SE-CNN + EWC | Channel-spatial hybrid SE | 99.63% | | |

## 5. CONCLUSION

This study automated and improved waste categorization procedures using deep learning, especially CNN. An innovative hybrid squeezing-based SE module improved waste item classification. The SE module, inspired by the human visual system's ability to focus on key details, was included to improve the model. This module's dynamic feature map re-calibration allowed the CNN to focus on trash's most informative features. To allow complicated data interdependencies, channel-wise and spatial-wise feature analysis were coupled to provide a flexible, robust framework. The motor that drove this model to unprecedented precision was the hybrid squeezing approach. The proposed method has been compared with both standard machine learning frameworks and state-of-the-art deep learning architectures via extensive experimentation. The findings were mind-blowing, as the classification accuracy of the proposed model is 99.63%, which is far higher than that of any other model. To address dynamic waste compositions, the model incorporated EWC, limiting catastrophic forgetting to < 1% while maintaining 98.5% accuracy on historical tasks. This adaptability ensures sustained performance as new waste types (e.g., e-waste, biodegradable materials) emerge. While fundamentally enhancing SE networks, future work will merge hybrid squeezing with attention mechanisms (e.g., Vision Transformers) to model global context beyond local feature recalibration. To further evaluate its practical application, research should focus on deploying the suggested methodology in real-world waste management facilities, considering scalability and integration problems. Automated waste management systems could be made more transparent and trustworthy by investigating interpretability issues and model explainability regarding trash item classification.

## REFERENCES


[1] J. Hsu, J. Wang, and M. Stern, "E-Waste: A Global Problem, Its Impacts, and Solutions," *Journal of Global Information Management*, vol. 32, no. 1, 2024, doi: 10.4018/JGIM.337134.

[2] R. Seif, F. Z. Salem, and N. K. Allam, "E-waste recycled materials as efficient catalysts for renewable energy technologies and better environmental sustainability," *Environment, development and sustainability*, 2024. doi: 10.1007/s10668-023-02925-7.

[3] C. Bircanoglu, M. Atay, F. Beser, O. Genc, and M. A. Kizrak, "RecycleNet: Intelligent Waste Sorting Using Deep Neural Networks," *2018 IEEE (SMC) International Conference on Innovations in Intelligent Systems and Applications, INISTA 2018*, Sep. 2018, doi: 10.1109/INISTA.2018.8466276.

[4] D. Kannan, S. Khademolqorani, N. Janatyan, and S. Alavi, "Smart waste management 4.0: The transition from a systematic review to an integrated framework," *Waste Management*, vol. 174, pp. 1–14, Feb. 2024, doi: 10.1016/j.wasman.2023.08.041.

[5] M. Toğaçar, B. Ergen, and Z. Cömert, "Waste classification using AutoEncoder network with integrated feature selection method in convolutional neural network models," *Measurement (Lond)*, vol. 153, Mar. 2020, doi: 10.1016/j.measurement.2019.107459.

[6] N. K. Trivedi *et al.*, “Early Detection and Classification of Tomato Leaf Disease Using High-Performance Deep Neural Network,” *Sensors 2021, Vol. 21, Page 7987*, vol. 21, no. 23, p. 7987, Nov. 2021, doi: 10.3390/S21237987.
[7] M. K. Chegeni, A. Rashno, and S. Fadaei, “Convolution-layer parameters optimization in Convolutional Neural Networks,” *Knowl Based Syst*, vol. 261, 2023, doi: 10.1016/j.knosys.2022.110210.
[8] A. D. Kulkarni, “Convolution Neural Networks for Phishing Detection,” *International Journal of Advanced Computer Science and Applications*, vol. 14, no. 4, 2023, doi: 10.14569/IJACSA.2023.0140403.
[9] M. Mudemfu and F. Wayne, “Intelligent Solid Waste Classification System Using Deep Learning,” MS thesis. Purdue University, Jul. 2023, doi: 10.25394/PGS.23786484.V1.
[10] C. Wang, J. Qin, C. Qu, X. Ran, C. Liu, and B. Chen, “A smart municipal waste management system based on deep-learning and Internet of Things,” *Waste Management*, vol. 135, pp. 20–29, Nov. 2021, doi: 10.1016/J.WASMAN.2021.08.028.
[11] Z. Li, F. Liu, W. Yang, S. Peng, and J. Zhou, “A Survey of Convolutional Neural Networks: Analysis, Applications, and Prospects,” *IEEE Trans Neural Netw Learn Syst*, pp. 1–21, Jun. 2021, doi: 10.1109/TNNLS.2021.3084827.
[12] O. Russakovsky *et al.*, “ImageNet Large Scale Visual Recognition Challenge,” *Int J Comput Vis*, vol. 115, no. 3, 2015, doi: 10.1007/s11263-015-0816-y.
[13] K. Brindhadevi, D. Barceló, N. T. Lan Chi, and E. R. Rene, “E-waste management, treatment options and the impact of heavy metal extraction from e-waste on human health: Scenario in Vietnam and other countries,” *Environ Res*, vol. 217, 2023, doi: 10.1016/j.envres.2022.114926.
[14] J. Hu, L. Shen, and G. Sun, “Squeeze-and-Excitation Networks,” *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pp. 7132–7141, Dec. 2018, doi: 10.1109/CVPR.2018.00745.
[15] J. Ji, B. Zhong, Q. Wu, and K. K. Ma, “A Channel-Wise Multi-Scale Network for Single Image Super-Resolution,” *IEEE Signal Process Lett*, vol. 31, 2024, doi: 10.1109/LSP.2024.3372781.
[16] B. T. Nguyen, S. T. Nguyen, and A. H. Vo, “Channel and spatial attention mechanism for fashion image captioning,” *International Journal of Electrical and Computer Engineering*, vol. 13, no. 5, 2023, doi: 10.11591/ijece.v13i5.pp5833-5842.
[17] A. G. Roy, N. Navab, and C. Wachinger, “Recalibrating Fully Convolutional Networks With Spatial and Channel ‘Squeeze and Excitation’ Blocks,” *IEEE Trans Med Imaging*, vol. 38, no. 2, 2019, doi: 10.1109/TMI.2018.2867261.
[18] Y. Pan and P. Zhan, “The Impact of Sample Attrition on Longitudinal Learning Diagnosis: A Prolog,” *Front Psychol*, vol. 11, 2020, doi: 10.3389/fpsyg.2020.01051.
[19] S. Mondesire and R. P. Wiegand, “Mitigating Catastrophic Forgetting with Complementary Layered Learning,” *Electronics (Switzerland)*, vol. 12, no. 3, 2023, doi: 10.3390/electronics12030706.
[20] J. Kirkpatrick *et al.*, “Overcoming catastrophic forgetting in neural networks,” *Proc Natl Acad Sci U S A*, vol. 114, no. 13, 2017, doi: 10.1073/pnas.1611835114.
[21] Y. Zhou, X. Tian, C. Zhang, Y. Zhao, and T. Li, “Elastic weight consolidation-based adaptive neural networks for dynamic building energy load prediction modeling,” *Energy Build*, vol. 265, 2022, doi: 10.1016/j.enbuild.2022.112098.
[22] Y. Zhang, Z. Lu, F. Zhang, H. Wang, and S. Li, “Machine Unlearning by Reversing the Continual Learning,” *Applied Sciences (Switzerland)*, vol. 13, no. 16, 2023, doi: 10.3390/app13169341.
[23] “Garbage classification.” Accessed: Oct. 30, 2023. [Online]. Available: https://www.kaggle.com/datasets/yashkangale20/garbage-classification
[24] C. Shorten and T. M. Khoshgoftaar, “A survey on Image Data Augmentation for Deep Learning,” *J Big Data*, vol. 6, no. 1, pp. 1–48, Dec. 2019, doi: 10.1186/S40537-019-0197-0/FIGURES/33.
[25] P. P. Malla, S. Sahu, and A. I. Alutaibi, “Classification of Tumor in Brain MR Images Using Deep Convolutional Neural Network and Global Average Pooling,” *Processes*, vol. 11, no. 3, 2023, doi: 10.3390/pr11030679.
[26] R. Azadnia, M. M. Al-Amidi, H. Mohammadi, M. A. Cifci, A. Daryab, and E. Cavallo, “An AI Based Approach for Medicinal Plant Identification Using Deep CNN Based on Global Average Pooling,” *Agronomy*, vol. 12, no. 11, 2022, doi: 10.3390/agronomy12112723.
[27] Y. Dogan, “A New Global Pooling Method for Deep Neural Networks: Global Average of Top-K Max- Pooling,” *Traitement du Signal*, vol. 40, no. 2, 2023, doi: 10.18280/ts.400216.