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A solid waste management system based on IoT using swin transformer with ant colony optimization model

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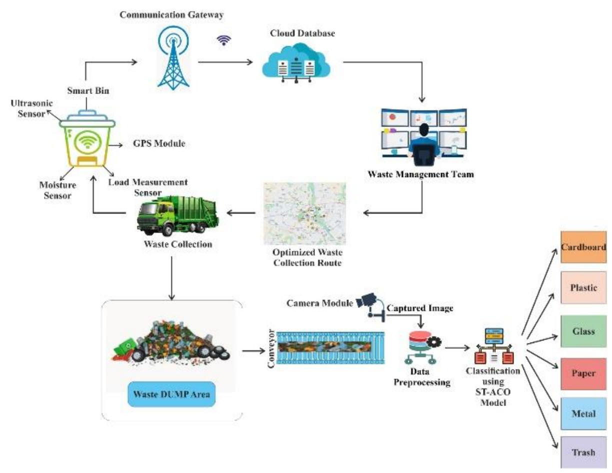
Graphical abstract



Abstract

The primary issue related to applications of smart cities is Solid Waste Management (SWM), which may be harmful to public health and the environment. Management of waste includes the disposal of trash through recycling and landfilling. SWM is a significant and challenging issue for ecosystems globally. Consequently, it is essential to develop an effective methodology to eradicate these problems or, mitigate them to a minimal extent. This paper introduces smart bins that are equipped with IoT-based sensors for the monitoring of waste level and classification, a feature that lacks in conventional methods, in contrast to previous techniques. This study develops a novel IoT-based SWM model using Swin Transformer (ST) v2 for waste classification and optimization algorithm for the route optimization process. The research work is proposed to address the challenge of SWM in smart cities by implementing IoT and deep learning technologies. Initially, the TrashNet dataset is collected to train and assess the research model. The real-time data from IoT-based sensors are preprocessed and analyzed in the waste management process. The Swin Transformer V2 is utilized for image classification. To improve the precision of the routing process, the Ant Colony Optimization (ACO) algorithm is employed. The evaluation of the research model was conducted based on parameters including accuracy, recall, f1-score, and precision. The proposed model also demonstrates exceptional accuracy (99.52), precision (99.10%), recall (98.86%), and F1-score (99.38%). These results were compared and validated with other models discussed in the literature review, and as compared, the research model outperformed all the other models.

Keywords: Solid Waste Management, IoT, Deep Learning, Swin Transformer V2, ACO, Sensors, TrashNet.

1. Introduction

The increasing population growth in cities is generating a tremendous amount of waste, which is causing problems for waste management (WM) systems in urban areas. One projection indicates that the global population is expected to attain 9.9 billion by 2050, representing an increase of almost 25% from the 2020 population of 7.8 billion. As the global population expands and a significant number of individuals migrate to urban areas, the smart cities concept is becoming relevant. The concept behind a "smart city" is the combination of multiple information and communication technologies, including the IoT, to sustainably manage public spaces and city services (Sosunova and Poras, 2022).

Figure 1 illustrates the prevalent domains of smart cities. It encompasses multiple intelligent sectors such as smart healthcare, smart energy, smart environment, and smart government. The fundamental principle of a smart city is an intelligent environment, mostly employed for technologies that address environmental degradation. A significant subject in the smart city paradigm is intelligent WM. Urban WM is a systematic process necessitating considerable effort and influencing social, economic, environmental, and efficiency factors. WM significantly influences the quality of life of the population. Sensors, GPS, and LED technology could be employed to optimize WM in garbage bins. The sensor autonomously alerts the operator of the optimal time to empty the garbage can and the designated path, disregarding traffic conditions (Whaiduzaman *et al.* 2022).

Figure 1. Overview of smart city domains

The enhancement of economic development and living circumstances in society are together leading to an increase in trash generation. The problem, which is concurrently a difficulty, is the necessity to manage them in compliance with the law (Czekala *et al.* 2023). Allied Market Research indicates that global WM is projected to expand at a rate of 6.2% by 2023, with accelerated growth anticipated in the growing Asia Pacific area. In Europe, this sector had growth above 30% in 2016, with further acceleration anticipated due to enhanced infrastructure and significant demand from several interested industries (Pardini *et al.* 2019).

Figure 2. Waste management process

The complexity of smart WM requires a complete multi-criteria strategy that includes data collecting, analytics, optimization, route planning, waste classification, decision support, and additional elements. A vast amount of this difficulty derives from services enabled with IoT that signify a shift from traditional technology such as geographic information systems, scheduling, and routing. The IoT can enable true innovation in trash management. Smart WM enhances energy efficiency, quality of life, and environmental safety, and decreases the consumption of resources (Szpillko *et al.* 2023). Waste can take many different forms, such as radioactive waste from nuclear reactors, infectious waste from hospitals, and solid waste from home sources. As seen in **Figure 2**, SWM encompasses waste material collection, recycling or disposal, transportation, and analysis (Visnu *et al.* 2022).

The daily collection of solid waste results in a waste of time, labour, and fuel when trash containers are vacant. Conversely, weekly solid waste collection may provide a risk of overflowing garbage bins. The complications in SWM underscore the urgent requirement for enhancements in the services provided by WM authorities, particularly in middle- and low-income nations (Akhram *et al.* 2021).

SWM has become a significant environmental concern worldwide, particularly in emerging nations. Consequently, there is a pressing need to establish an efficient SWM system to conserve resources and safeguard environmental and public health. The environmental issues associated with SWM are complex to address due to their diverse characteristics. The background research reveals that the SWM has concentrated on employing advanced technologies, including the IoT, information technology, deep learning (DL) and machine learning (ML), which have significantly enhanced the efficiency of various SWM operations (Shahab *et al.* 2022).

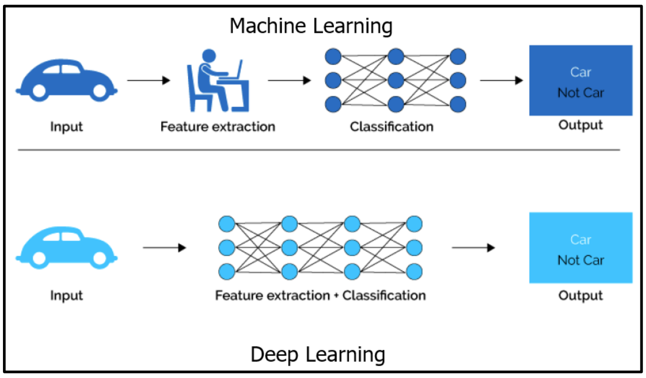


Figure 3. Example of Machine and Deep Learning Approach

Trash bins are installed to manage solid waste efficiently. Conversely, inadequate management of trash bins results in significant issues such as overflow. Effective WM profoundly influences the general welfare of the general population (Alshaikh and Abdelfatah, 2024). Utilization of sensors, GPS, and LED technology can facilitate the efficient management and oversight of waste within garbage receptacles. Sensors are the essential element of IoT-enabled WM and are included in the majority of research initiatives. They are designed to quantify specific physical parameters such as (i) capacity, (ii) temperature, (iii) weight, (iv) humidity, (v) chemical processes, and (vi) pressure (Anagnostopoulos *et al.* 2017). DL and the IoT are integral to contemporary trash management initiatives. Deep learning has recently made significant progress, especially in the classification of images and object detection. The ML and DL methodologies are illustrated in **Figure 3**.

The significance of SWM is evident in its capacity to reduce environmental risks, preserve resources, and maintain public health standards. As urban populations expand, the quantity of waste generated rises significantly, rendering effective solid waste management a crucial requirement. This study addresses the critical need for novel solutions in this SWM field. Despite these innovations, considerable gaps persist in the execution of real-time waste classification integrated with effective route optimization. The advancement in SWM has been improved with the integration of IoT, DL, and optimization algorithms. Existing research works were focused on using sensors with conventional ML models. However, these models often struggle from reduced efficiency and accuracy. This research addresses the issues and gaps by presenting IoT-enabled smart bins for real-time waste classification with Swin Transformer V2 and Ant Colony Optimization for route optimization. The suggested approach exhibits enhanced accuracy and efficiency, surpassing current methods in the literature.

1.1. Problem statement

In recent years, SWM has emerged as a significant concern due to increased industrialization and urbanization, resulting in an increased volume of waste generation. Among the various challenges in this domain, waste segregation has emerged as a major problem in existing IoT-based models. Inefficient and inaccurate classification of waste types hampers the effective disposal, recycling, and management of solid waste, leading to environmental pollution and resource wastage. The integration of advanced technologies in waste segregation remains an unmet need, which necessitates the development of a more efficient and precise waste classification system to address these limitations.

The research objectives are given as follows.

To develop a novel DL-based SWM model for monitoring the smart bins and classifying the wastes.

To utilize the TrashNet dataset and sensor data for training and evaluating the performance of the proposed model.

To enhance the pre-processing technique of a model by using the Data scaling method.

To improve the performances and efficiency of the model by implementing the Swin Transformer V2 technique for classification.

To apply the ACO algorithm for the route optimization process.

To compute the efficiency of the proposed model utilizing captured trash image data.

To assess the research model's performance regarding accuracy, specificity, F1-score, recall, and precision.

To evaluate and verify the model's performance against current methodologies.

This introduction part discusses the waste management in smart cities, integration of IoTs, applications of ML and DL in SWM, and the concept of proposed research. The remaining sections will be as, section 2 discusses the related works on SWM and IoT integrated models, section 3 discusses the research methodology and implementation, section 4 includes the performance analysis of the research model and section 5 presents the conclusion of the work.

2. Literature review

This section presents the analysis of various current models developed for the SWM using DL and ML models. Based on the analyzed review, a comparative analysis is provided in **Table 1**. A real-time trash monitoring system employing a DL framework and IoT was introduced by (Rahman *et al.* 2022). This model was categorized as an architectural framework for the classification of waste, employing the Raspberry Pi with a camera module and a smart trash bin with a microcontroller equipped with several sensors for waste monitoring in real-time. The smart trash bin comprises a load measurement sensor, an ultrasonic sensor, and a microcontroller. The Convolutional Neural Network (CNN) was employed for the classification of images to categorize waste.

A CNN-based intelligent system utilizing LoRa-GPS and TensorFlow Lite in IoT for WM was proposed by (Sallang *et al.* 2021). An SSD MobileNetV2 Quantized was employed and trained using a dataset for waste classification. The approach was included with an IoT-based sensor and a LoRa-GPS module that accurately determined bin position and transmitted bin status across extended distances. The LoRa in the smart bin transmits the bin's status to the LoRa receiver at a frequency of 915 MHz. CNN were employed for processing the image and object recognition. The dataset, TrashNet, comprises 6 categories: glass, plastic, cardboard, paper, metal, and trash.

The bin-level monitoring system for SWM based on IoT was introduced by (Ramson *et al.* 2021). An independent, easily connectable IoT solution for tracking the unfilled levels of trash bins from a central monitoring station was designed and tested. The terminal sensor nodes of the system, designated as Bin Level Monitoring Units (BLMUs), are mounted in each garbage bin to monitor the unfilled level. Each BLMU assesses the unoccupied capacity of the waste bins and relays this information to a wireless access point unit (WAPU) and it acquires empty-level data from many BLMUs and transmits it to the central server for storage and analysis.

Blockchain-Enabled Vehicle Ad Hoc Networks (VANET) for Intelligent SWM were introduced by (Saad *et al.* 2023). Advanced ultra-high frequency technology was employed in conjunction with IoT devices for the tracking of waste vehicles and the identification of waste bins in real-time. Geo-fencing techniques were utilized for the surveillance and timely collection of waste from designated dumping locations. Finally, blockchain technology was utilized in the solutions to enhance the security, reliability, and trustworthiness of machine-to-machine (M2M) communication among IoT devices.

A unique approach for waste detection and classification utilizing Ensemble Neural Networks was proposed by (Geetha *et al.* 2022). The model was trained using publicly accessible trash datasets that had images of various trash objects. The preprocessed images are subsequently transmitted to four neural network modules: Mask Region-Based CNN (RCNN), Very Deep CNN (VGG16), and You Only Look Once (YOLO), Structure from Motion (SFM). Based on images captured by users on their devices, the trained model was installed into a mobile application that geotags waste.

By (Ali *et al.* 2020), monitoring municipal SWM systems and a smart waste bin utilizing IoT technology was proposed. This system efficiently gathers waste, identifies fires in waste materials, and predicts future waste production. An IoT device enables the management and surveillance of electric bins, which are wirelessly linked to a central hub to convey data on the bins' fill levels and locations. Results indicate that waste collection via the IoT-based system was more efficient than traditional methods.

By (John *et al.* 2022), a smart monitoring and prediction system for waste disposal based on IoT was presented, utilizing commercially available components which can be affixed to bins of any size to measure fill levels. The Arduino microcontroller was utilized to connect ultraviolet (UV) and infrared (IR) sensors, a Global Positioning System (GPS) module and weight sensors, to monitor bin status at specified intervals. An advanced neural network method, specifically Long Short-Term Memory (LSTM), was employed to forecast and categorize forthcoming waste based on waste creation patterns. The JavaScript Application Programming Interface (API) was utilized to dispatch notification messages in web applications within browsers that enable service employees to operate. The stacked LSTM was thus a superior model for the prediction of fill levels.

An IoT-based SWM system utilizing computer vision was launched by (Mookkaiah *et al.* 2022). The classification was carried out with CNN architecture and ResNet inception. ResNet V2 facilitates the training of extensive datasets in deep neural networks, resulting in enhanced accuracy and reduced error rates in mapping. Furthermore, mixed hybrid pooling techniques and batch normalization were integrated into the CNN to enhance stability and achieve state-of-the-art performance.

A classification approach based on ensemble learning for predicting household solid waste generation was proposed by (Nammoun *et al.* 2022). It integrates the benefits of a meta-regressor model and hyperparameter optimization to precisely forecast the weekly waste generation of homes in urban areas. Optimization of the hyperparameters of models was conducted using an algorithm called Optuna, and the output from the optimized individual ML models was utilized for training the meta-linear regressor. This approach outperformed the traditional methods, such as SARIMA, LightGBM, NARX, ETS, KNN, XGBoost, RF, SVR, and ANN, in predicting future waste generation, with an R2 score (0.8) and 0.26 as a mean percentage error.

An innovative DL algorithm for segregating garbage was developed by (Gunaseelan *et al.* 2023). The image classification was performed via a modified ResNeXt model. ResNeXt enhances image classification performance by utilizing parallel branches with diverse filter sizes, thereby capturing a broader range of information in the input image. The CNN was integrated with a modified ResNeXt trained on substandard images. The waste container was equipped with an ultrasonic sensor for level detection, a stepper motor for lid operation, a toxic gas sensor, solar panels for energy storage, and a Raspberry Pi camera with board. The findings indicate that a model can efficiently and accurately classify waste into suitable categories.

The Waste Classification Utilizing Image Recognition with a DL Neural Network Model was presented by (Malik *et al.* 2022). The classification architecture employed was EfficientNet-B0, optimized for adapting images pertinent to certain demographic regions for effective classification. The tuning of the model was done using transfer learning provides a customized classification model, thoroughly optimised for a specific location. The model utilized the output from the penultimate layers. The result functions as the inputs to the CNNs in the developed approach was then trained on the other data set.

A real-time SWM and categorization mechanism utilizing an advanced technique (SWMACM-CA) was introduced by (Cheema *et al.* 2022). It employed the IoT, DL, and advanced methodologies to categorize and separate waste materials in a disposal site. A camera collects an image of the trash yard and transmits it to an edge node to generate a waste grid. The grid cell image segments serve as a test image for trained DL models, enabling the prediction of specific waste items. The DL algorithm employed for the project was the Visual Geometry Group model with VGG 16.

The ML-Based Sustainable Application of SWM in IoT utilizing Modified Cuttlefish Swarm Optimization (MCSOML-SWM) was developed by (Al Duhayim, 2023). The MCSOML SWM method seeks to identify several types of solid waste and facilitate intelligent WM. A single-shot detector facilitates effective object recognition. A deep CNN-based MixNet model was utilized to generate feature vectors. Due to the laborious nature of trial-and-error hyperparameter tuning, the MCSO algorithm was utilized for automated hyperparameter optimization. It employs a support vector machines for trash classification in the study.

A DL Methodology for Classifying Recyclable Products in Sustainable WM was introduced by (Ahmad *et al.* 2023). The trash classification models were developed utilizing CNN methods, together with pre-trained models such as MobileNetV2, ResNet50V2, and DenseNet169. A dataset of 5000 images of refuse and waste materials was utilized for the training and evaluation of the models. To achieve optimal results, the hyperparameters were adjusted and cross-validation was performed using Randomized Search CV to identify the most effective hyperparameters.

A ML model for SWM in Urban Sri Lanka was introduced by (Baddegama *et al.* 2022). The system deployed smart bins equipped with sensors to track waste levels and leveraged machine learning to enhance waste collection routes, hence increasing operating efficiency and decreasing expenses. The research illustrated the capability of using IoT and ML to tackle urban garbage issues. The model's accuracy was 89%. Nonetheless, its versatility concerning other waste categories and wider geographical settings has yet to be investigated.

(Sayem *et al.* 2024) focused on enhancing waste sorting and recycling through DL for classifications and detections. They highlighted the importance of intelligent waste management amid growing pollution concerns and identified limitations in existing datasets. The authors presented a new dataset with 28 recyclable categories and 10,406 images. The proposed dual-stream network achieved 83.11% accuracy, outperforming other models. Additionally, the GELAN-E model for waste detection achieved a mean average precision (mAP50) of 63%, demonstrating significant progress in intelligent waste management.

(Rahmatulloh *et al.* 2024) addressed the rising problem of trash management by emphasizing real-time waste identification with deep learning techniques. The authors highlighted the deficiencies of conventional waste sorting techniques and underscored the necessity for automated solutions such as computer vision. A model was developed to categorize waste according to visual features, distinguishing recyclable, non-recyclable, hazardous, and organic waste. The model attained a precision of 0.801, a mean Average Precision at 0.5 of 0.868, and a mean Average Precision at 0.5:0.95 of 0.618.

Table 1. Critical Review of Reviewed Studies

Approach	Application	Advantages	Disadvantages
CNN	Real-time waste classification	Achieved 95.31% waste categorization accuracy	Only two sensors were used in the prototype
CNN Tensorflow	IoT-based smart waste bin with LoRa-GPS module	Accurate bin location tracking and transmission over long distances	Small dataset size limits the generalizability
BLMU	Bin-level monitoring using IoT for SWM	Long battery life (434 days) and low cost	Limited transmission range
Blockchain with IoT	Real-time waste tracking and geofencing	Improved security, reliability,	Data transmission challenges
Ensemble Neural Networks	Mobile app for geotagging and classification of waste items	High classification accuracy	Computational complexity due to the ensemble of models
IoT-based system	Smart waste bin monitoring	Efficient waste collection,	Scalability issues for larger areas
LSTM	IoT-based waste bin monitoring	Accurate waste forecasting and classification	Dependence on connected infrastructure for timely notifications
ResNet V2	IoT-based waste classification and image processing using CNN	Enhanced accuracy with reduced error	Reliant on pre-trained ImageNet dataset
Ensemble Learning	Prediction of household solid waste generation	High precision	Computational overhead due to hyperparameter optimization
Modified ResNeXt	Smart waste bin for image-based waste classification	Very high classification accuracy	Expensive hardware requirements
EfficientNet-B0	Waste classification based on region-specific tuning	Lightweight model with high location-specific performance	Lower accuracy
VGG16	IoT-based waste classification	High classification accuracy	Dependency on cloud servers for processing
MixNet with SSD	Intelligent waste classification using MCSOML-SWM	automated hyperparameter tuning	Complex hyperparameter tuning process
CNN (MobileNetV2, ResNet50V2, DenseNet169)	Recyclable product classification	Effective hyperparameter optimization	Performance dependent on data diversity

The current research works have been designed with conventional ML and DL algorithms, the proposed research work makes use of a novel DL model called Swin Transformer for classifying waste accurately and ACO for effective and dynamic route optimization as an advancement. Through attaining greater results and superior performance in SWM, this research will be considered as a major step in improving SWM in smart cities.

3. Proposed methodology

This study primarily aims to develop an intelligent SWM system for monitoring the waste's fill level, weight, and classification. **Figure 1** depicts the proposed methodology of the SWM system. The smart waste bins are equipped with IoT-based sensors to monitor waste levels. WM authorities gather waste from all the commercial and residential sites. Second, the garbage dump's image is captured utilizing a camera. Further, the images are fed to the DL model for the waste classification process. Deep learning technology facilitates the classification of waste categories from images. Classifying waste into appropriate groups facilitates the identification of reusable materials. Recognizing recyclable materials enables their use without degradation. In the image classification field, DL systems achieve outstanding outcomes.

An ultrasonic sensor is positioned on top of the smart bin to assess the waste level within the bin. A load-measuring sensor is positioned at the base of the bin to ascertain the weight of the trash. A Moisture Sensor measures the moisture content in the trash. The GPS module is utilized to determine the location of the smart bin. The data from three sensors is stored in the cloud via a Wi-Fi-based communication gateway. The WM system team can retrieve data from the cloud for waste collection. This team transmits the status and route of the smart bin to the truck operator for the garbage collection operation. To improve the precision of the routing process, an ACO algorithm was employed for timely Waste Collection Vehicle Routing. ACO was selected over other metaheuristic techniques for several reasons:

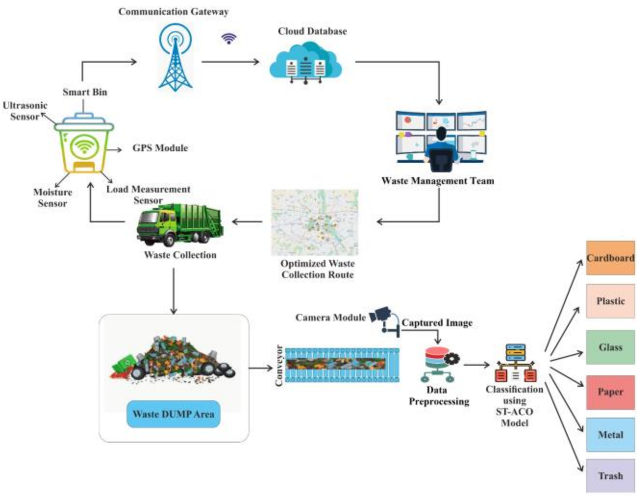


Figure 4. Proposed Architecture of IoT-Based SWM System

Adaptability: ACO adapts well to dynamic environments and real-time decision-making, which is crucial for waste management systems.

Scalability: ACO can efficiently handle large-scale optimization problems, such as route planning for multiple trucks across an extensive urban area.

Proven Effectiveness: ACO has been widely used in logistics and transportation systems for route optimization, making it a reliable choice for waste collection vehicle routing.

After the accumulation of waste from many bins, it is dumped across a designated region. The presence of several garbage objects in a garbage dump complicates the real-time segregation of waste materials. This research incorporates an effective deep-learning classification model for garbage segregation. The waste collection is placed on a conveyor for categorization. A compact camera module is positioned above the conveyor to capture images of the waste. The acquired images are input into the DL process known as data pre-processing. The image is pre-processed using a data scaling approach. The pre-processed data serves as input for the classification procedure. The Swin Transformer V2 is employed for garbage classification. This research categorizes waste into six types: cardboard, metal, glass, paper, plastic, and trash.

3.1. Sensor description

The primary function of IoT-based sensors in smart bins is to monitor their volume, weight, and contents. The primary method employed for monitoring the filling level of the container is ultrasound. The load cell is utilized to measure the bin's weight. To measure the moisture level in the garbage moisture sensor is utilised. An ultrasonic sensor transmits the ultrasound through the atmosphere at 40,000 Hz; if any obstacle obstructs its route, the ultrasound reflects to the sensors, adhering to the principles of sound reflection. The load measuring sensor measures the weights of items. The formula was typically utilized to convert the sensor's output voltage levels, estimated in mV/V, to calculate the detected weight. Users must select their preferred units, such as kilograms, grams, or pounds. A moisture sensor is employed to detect the moisture levels in the garbage to determine if the waste is moist or dry.

3.2. Description of datasets

This study utilizes the publicly accessible TrashNet dataset from Github. The dataset is hand-collected and around 3.5GB in size. It has six categories: metal, glass, cardboard, paper, and waste. Collectively, these categories comprise 99% of recycled materials. This library presently comprises 2,527 images of garbage. Every image has 512×384 pixels that could be modified or scaled in data. The images were obtained by positioning the objects on the background of white board, utilizing either ambient room lighting or sunshine. This study utilizes a subset of the dataset encompassing six waste categories: cardboard, plastic, metal, glass, paper, and trash. The data is divided into two sets: testing and training, with proportions of 75% and 25%, respectively. Nevertheless, for the real-time evaluation of the proposed model, the entire dataset was trained, and test images were taken in real-time, namely (Cheema *et al.* 2022). However, for real-time testing of the proposed model, the entire dataset was trained, and test images were taken in real-time specifically. **Table 2** illustrates the class distribution within each subset of the data.

Table 2. Training and Testing Subset Sample Distributions

Class	Training	Testing	Total
Metal	308	102	410
Glass	376	125	501
Trash	103	34	137
Plastic	362	120	482
Total	1149	381	1530

3.3. Data preprocessing

The pre-processing is a vital stage in the training of DL models. Preparing the data before transfer to the classification model is known as data pre-processing. The obtained time series data are normalized using a Min-Max normalization method. This aids in eliminating the units in the collected data or the influence of varying scales. The Min-Max normalization is utilised to scale data value within a specified range (zero to one). This normalization technique first subtracts the minimum value from data points and then divides by the range. Min-Max scaling is to acquire every feature to the standard limit. Min-Max is a transformation technique employed to the original data. Equation (1) presents the Min-Max normalization method formula.

$$y_{norm} = \frac{y - min}{max - min} \quad (1)$$

Where,

y as the original data,

y_{norm} as the normalized output of the given sequence y,

max and *min* are maximum and minimum values of y, respectively (Li *et al.* 2023).

For this research, the trash dataset originally consisted of images with dimensions of 512 x 384. To ensure compatibility with the Swin Transformer V2 classification algorithm, which requires an input size of 256 x 256, the Min-Max data scaling technique was employed to resize the images. This step was crucial to align the dataset with the model's input requirements, facilitating accurate and efficient classification.

3.4. Classification using swin transformer V2

This research uses a DL model for IoT-based sensor image categorization that is based on ST-v2. The improved version of ST is called ST-v2. By increasing the model's size and ability to adjust to various window sizes and image resolutions, it surpasses version 1.0. The shifted window multi-head self-attention (SW-MHSA) module and window multi-head self-attention (W-MHSA) module are two of the Swin Transformer modules that are integrated into the block. Furthermore, using ST-v2's cosine (Q, K)/η method to calculate Attention in the Transformer block, where η was a learnable parameter which is not shared across blocks. Normalization is a built-in feature of the cosine operation, which helps to further stabilize the attention output values.

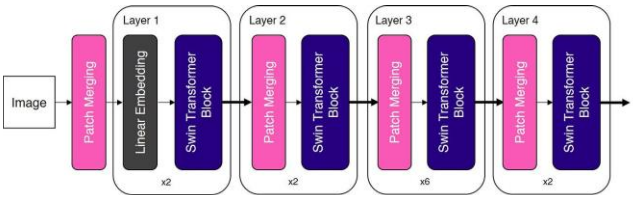


Figure 5. The Overall Architecture of Swin Transformer V2

The general layout of the ST-v2 is shown in **Figure 5**. The patch partitioning module initially divides the 256 × 256 input image into 4×4 non-overlapping patches. After that, a linear embedding layer is used to project these patches into C dimensions and handle them as "tokens." These patch tokens are subjected to 2 successive ST-v2 blocks with a computation. A "stage" comprises an ST-v2 block and linear embedding layer. Its architecture is similar to CNNs' layer structures, with each stage seeing a doubling of channels and a halving of resolution. The ST creates deeper networks by combining patch layers to reduce the number of tokens needed to construct hierarchical representations.

The model employs a greater resolution of 256 × 256. The benefit of this is that the network may utilize additional features, and enhancing the extraction of feature capabilities of the network elevates the model's performance. Each block consists of 2 units, each including 2 normalization layers (LayerNorm), a multi-layer perceptron (MLP) layer and a self-attention module. The two successive modules in the block are the W-MHSA module and the SW-MHSA module. It employs the W-MHSA, while the second unit utilizes the SW-MHSA module. Whereas the Swin Transformer uses residual connections after each module, the ST-v2 adds a Layer Norm layer after each MHSA module and MLP layer.

3.4.1. Shifted window-based self-attention (SA)

A technique for computing SA inside localized windows was employed to reduce the complexity of computation and enhance modelling performance. A moving window approach is employed to compute SA in this experiment. In W-MHSA, the relationship was linear, and the computational load was manageable. Considering every window has D×D patches, the windows are arranged non-overlappingly to partition the image into equal segments. The worldwide computational complexity of the MHSA module and the W-MHSA module, as depicted in an image with hardware patches, are as follows:

$$\Omega(MHSA) = 4cdA^2 + 2(cd)^2 A \quad (2)$$

$$\Omega(W - MHSA) = 4cdA^2 + 2M^2 cdA \quad (3)$$

Where $g \times w$ is an image's total patch count, and C stands for a channel of patch channels. Equation (3) has a linear complexity when D is constant. In contrast, Equation (2) has a quadratic complexity regarding the total patches $g \times w$.

The window-based SA model lacks connections of cross-window, neglecting the interrelations among distinct windows and constraining modelling potential. To create cross-window connections while preserving the computational efficiency of non-overlapping windows, this approach rotates between 2 partition configurations in subsequent ST V2 blocks. As seen in **Figure 6**, the 1st module splits the 8 × 8 feature maps into 2 × 2 window, each of which is 4 × 4 (D = 4), utilizing a standard windows partitioning technique that starts at the upper-left pixels. Next, by displacing the window from an ordinary partitioned window by $\left[\frac{D}{2}\right], \left[\frac{D}{2}\right]$ pixel, the following module adopts an offset window configuration from the window configuration of the previous layer. The boundary of the preceding window is also taken into consideration by the self-attention measurement in the new window, which takes into account the connection information between several windows. The calculated consecutive ST V2 blocks are as follows, utilising the shifted window partitioning method:

$$\hat{Y}^l = W - MHSA\left(LN\left(Y^{l-1}\right)\right) + Y^{l-1} \quad (4)$$

$$Y^l = MLP\left(LN\left(\hat{Y}^l\right)\right) + \hat{Y}^l \quad (5)$$

$$\hat{Y}^{l+1} = SW - MHSA\left(LN\left(\hat{Y}^l\right)\right) + \hat{Y}^l \quad (6)$$

$$Y^{l+1} = MLP\left(LN\left(\hat{Y}^{l+1}\right)\right) + \hat{Y}^{l+1} \quad (7)$$

where $\hat{Y}^l$ and Y^l reflect the output characteristics of the SW-MHSA module and MLP in the l layer, respectively; and

W-MHSA and SW-MHSA using shifted window and normal partitioning processes.

The window partitioning approach generates several new windows, some of which are smaller than D×D. A common approach for computing self-attention involves flattening all windows to D×D dimensions. This approach, however, yields an increased number of windows. The window transformation technique significantly increases the model's computing expense as the number of windows increases from 2×2 to 3×3. To manage this problem, the improved batch computation method that moves cyclically to the left top is applied, as shown in **Figure 6**. The batch-calculated windows may encompass several non-contiguous windows in the feature map following the shift. Consequently, a masking technique was employed to hide the self-attentions computations for all the sub-windows. The computational performance for cyclic shifting is improved while the total batch windows and standard window partitions remains unchanged.

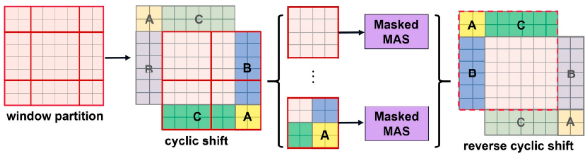


Figure 6. Batch Computations for SA in Shifted Windows Partition

3.4.2. PolyLoss (PL)

The PL function has demonstrated superiority over focal loss and cross-entropy loss in several tasks, including the classification of 2D imaging, 3D detection, object recognition and instance segmentation. Consequently, in this experiment, PL is employed as a loss function for the ST to enhance the accuracy of the SWM classification model. The polynomial coefficients (PC) are denoted by, and the PL formula is articulated as follows:

$$L_{poly} = \beta_1(1-Z_t)+\beta_2(1-Z_t)^2+\ldots+\beta_N(1-Z_t)^N \\ +\ldots=\sum_{j=1}^{\infty}\beta_j(1-Z_t)^j \tag{8}$$

This formula requires the modification of an infinite number of PC. Adjusting numerous PC would still yield an excessively huge search space, making it unfeasible. Moreover, cross-entropy loss does not outperform the simultaneous tuning of several coefficients. This issue is resolved by altering the major PC in the loss called cross-entropy while keeping the remaining coefficients constants. The equation for loss was represented as the Poly-N, with N indicating the total coefficients that require alteration.

$$L_{poly-N} = (\alpha_1+1)(1-Z_t)+\ldots+\left(\alpha_N+\frac{1}{N}\right)(1-Z_t)^N \\ +\frac{1}{N+1(1-Z_t)^{N+1}}+\ldots=-\log(Z_t)\sum_{j=1}^{N}\alpha_j(1-Z_t)^j \tag{9}$$

Specifically, revise the *j* PC of the cross-entropy loss from 1/j to $\frac{1}{j}+\alpha_j$, where $\alpha_j \in \left[-\frac{1}{j},\infty\right]$ is a perturbation term. Equation (9) illustrates the precise computation of the first N polynomials, eliminating concerns over an infinite count of high-order ($j > N + 1$) coefficient. The most substantial improvement was achievable for initial polynomial terms. The conclusive PL equation was presented below, integrating additional simplified version of the Poly-N equation, and focusing on the assessment of Poly-1, whereby just the initial PC is modified (Li *et al.* 2023):

$$L_{poly-1} = (1+\alpha_1)(1-Z_t)+\frac{1}{2}(1-Z_t)^2 \\ +\ldots=-\log(Z_t)+\alpha_1(1-Z_t) \tag{10}$$

In this experiment, SWM image classification was accomplished using the value of $\alpha_1 = 2$.

3.5. Optimization using ant colony optimization algorithm

The ACO method is a metaheuristic approach that employs a group of artificial ants to address various optimization challenges. ACO has been employed to address issues such as the Quadratic Assignment Problem, Knapsack Problem, Traveling Salesman Problem (TSP), and Vehicle Routing Problem, among others. This research employs ACO to improve the SWM system by mitigating the vehicle routing difficulty.

The following section will briefly outline the methodology for addressing issues by emulating the action of ant. Assume a full graph *G*, wherein *V* represents the node's set and *E* denotes the edges set. ACO was based on a natural phenomenon wherein ants consistently identify the small route between a food source and their colony, utilizing pheromones deposited on the ground by preceding ants as a guide. When multiple options exist for selecting a subsequent node, an ant probabilistically selects one with highest pheromone concentrations. Let p_0 be a fixed number where $0 \le p_0 \le 1$ and *p* be a random number between 0 and 1. If $p \le p_0$, then, according to, ant *k* in node *i* chooses node *j* such that,

$$m = \underset{q\in R_{k(i)}}{\operatorname{argmax}}\left[\gamma(i,q)\right]^{\mu}.\left[\rho(i,q)\right]^{\omega} \tag{11}$$

where,

μ denotes the relative significance of a pheromone,

ω denotes relative significance of heuristic functions,

$R_{k(i)}$ denotes the nodes set to which ant *k* could transition from node *i* while adhering to every stipulated constraint.

$\gamma(i, q)$ denotes the concentration of pheromone between nodes *q* and *i*.

$\rho(i, q)$ was the distance among nodes *i* and *q* heuristic function.

Conversely, if $p \ge p_0$, the selection of the subsequent node occurs randomly with the following probability:

$$q_k(i,q) = \begin{cases} \dfrac{\left[\gamma(i,q)\right]^{\mu}.\left[\rho(i,q)\right]^{\omega}}{\sum_{q\in R_{k(i)}}\left[\gamma(i,q)\right]^{\mu}.\left[\rho(i,q)\right]^{\omega}}, & if\ q\in R_{k(i)} \\ 0, & otherwise \end{cases} \tag{12}$$

Upon node selection, an ant produces pheromone throughout the paths, namely, edge linking *i* and *q* in the present instance. The pheromone density along the shortest path will escalate more rapidly than on alternative courses due to a higher deposition rate. The pheromone is volatile and dissipates with time. The pheromone concentration on other routes will be significantly lower than that on the predominantly utilized route, namely, the shortest path. Examine the evaporation rate η. Following all the rounds, the pheromones concentration was revised accordingly. When edge (*i*, *q*) was utilized in the iteration, then it has

$$\gamma(i,q)=\gamma(i,q)+\eta.\gamma_0 \tag{13}$$

where γ_0 is the pheromone's initial amount. A specific level of pheromones evaporate from every edge (Islam and Rahman, 2012). The formula of pheromones evaporation was presented as follows:

Initialize

Step 1: Collect real-time data from IoT waste bins

Initialize waste bins with sensors

Collect sensor data from all bins

Step 2: Preprocess the TrashNet dataset

Load TrashNet dataset

Split data into training (75%) and testing (25%)

Preprocess the data (min-max scaling, remove noise)

Step 3: Train the ST-v2 model

Initialize ST-v2

Train the model with the training data

Test the model with testing data

Output evaluation metrics

Step 4: Classify waste using the trained model

For each bin:

If the bin is full:

Classify waste type using Swin Transformer V2

Step 5: Optimize waste collection routes using ACO

Initialize ACO parameters (ants, pheromone levels, iterations)

For each ant:

Generate route starting from waste collection depot

Select bins based on distance and pheromone levels

Update pheromone levels based on route efficiency

Step 6: Select the best route and dispatch waste collection trucks

Choose the optimal route based on ACO results

Assign trucks to the optimal route

Step 7: Real-time monitoring and route optimization

Continuously monitor bins

If the bin is full:

Recalculate routes using ACO

END

$$\gamma(i,q)=(1-\eta)\gamma(i,q) \tag{14}$$

The proposed IoT-based SWM model starts by collecting real-time data from sensors in waste bins and monitoring fill levels and locations. The TrashNet dataset is preprocessed using scaling and cleaning techniques to prepare it for training the Swin Transformer V2 model, which classifies different types of waste. For waste collection, ACO is used to generate optimal routes for waste collection trucks based on bin status and location.

The system continuously monitors the bins in real-time, recalculating routes using ACO whenever a bin is full to ensure efficient waste collection.

4. Experimental analysis

4.1. Experimental setup

This section provides an overview of the evaluation and performance analysis conducted on the proposed model. The research model was tested in an experimental configuration using a PC with Windows 10, a 64-bit operating system, an Intel(R) i7 processor running at 4.60 GHz, and 16GB of RAM. The model was developed using the Python 3.11.4 64-bit tool and relied on the Pandas, Numpy, and Scikit-learn modules. The achieved outcomes for the proposed model are compared and verified against the existing SWM models.

4.2. Evaluation metrics

The evaluation of the research model was conducted based on parameters including accuracy, precision, recall and f1-score. The metrics are calculated using the values of True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN), which are the four categories utilized to identify the results of the detection.

Accuracy quantifies the ratio of accurate classifications out of the overall data.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{15}$$

Recall is the proportion of properly classified data to the total data analyzed.

$$Recall = \frac{TP}{TP + FN} \tag{16}$$

F1 score, a statistical measure utilized to assess the positive class detection accuracy. The f1-score is the probability of properly classified positive data samples to every sample identified as positive.

$$F1\text{score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{17}$$

Precision can be measured by a ratio of sample's true positive to the total samples recognized as positives, specifically focusing on the correct detection of negative samples as positive.

$$Precision = \frac{TP}{TP + FP} \tag{18}$$

4.3. Performance evaluation

This study categorizes waste into six types: cardboard, metal, glass, plastic, paper, and trash. The varying accuracy values for these six classes are presented in **Table 3**.

Table 3. Accuracy of the 6 Classes

S.no	Class	No. of test images	Accuracy
1	Glass	56	95.66
2	Cardboard	72	96.02
3	Metal	45	95.82
4	Plastic	66	95.22
5	Paper	78	95.51
6	Trash	30	94.89
Average	99.52		

The performance analysis of the waste classification model shows consistently high accuracy across different waste categories. For Glass, with 56 test images, the model achieved an accuracy of 95.66%, while Cardboard, with 72 test images, reached the highest accuracy of 96.02%. Metal and Plastic classifications showed slightly lower accuracies of 95.82% and 95.22%, respectively. Paper, with 78 test images, recorded an accuracy of 95.51%, and Trash, with the least number of test images (30), had an accuracy of 94.89%. The model's overall performance indicates a highly reliable classification mechanism, achieving an impressive average accuracy of 99.52%, which demonstrates its robustness in distinguishing various waste materials effectively. **Figure 7** represents the depiction of the classification accuracy of trash classes.

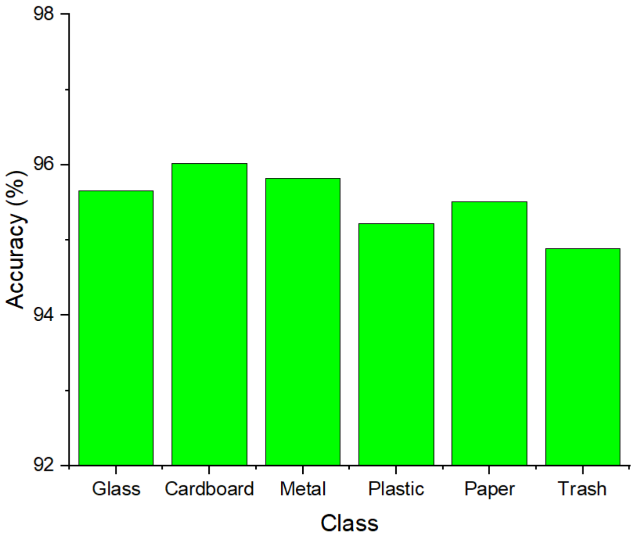


Figure 7. Classification of Trash Classes Accuracy

A series of experiments to determine the empty levels and weights of the garbage were conducted. **Table 4** illustrates a corresponding experimental result from the ultrasonic sensor and the load measurement sensor.

Table 4. Results of the Load Measurement and Ultrasonic sensors.

No. of trials	Delay (min)	Level of the Waste (cm)	Free level (%)	Waste Weight (kg)
1	10	30.00	More than 90%	0.650
2	8.2	24.8	More than 80%	0.950
3	5.5	16.6	More than 45%	1.200
4	2.5	10.20	More than 20%	1.900
5	1.0	5.00	More than 10%	2.500

Table 5. Performance Comparison with Current Models

Models	Accuracy	Precision	Recall	F1-score

CNN	95.31	-	-	-
CNN-Tensorflow	95.14	-	-	-
Ensemble method	93.65	91.23	66.71	-
CNN+ResNet	94.44	-	90.41	92
CNN+ResNext	98.9	-	-	-
SWMACM-MA	96	-	-	-
MCSOML-SWM	99.34	97.97	97.41	97.67
ResNet50V2	98.95	98.35	93.38	98.38
DLSODC-GWM	98.61	95.23	92.29	94.72
PSO-ANN	96.50	92.2	94.2	92.1
GA-SVM	87.2	89.4	85	89.7
RF	89	-	-	-
2S_DenseViT + GELAN-E	83.11	83.33	-	83.05
Proposed model	99.52	99.10	98.86	99.38

Table 4 focuses on how the system functions with respect to time. For evaluation, five samples were collected, including time delays in minutes, trash levels in centimetres, empty levels in %, and waste loads in kg. The 2 output data points, namely the empty levels & the weights of wastes, would be transmitted to the relevant WM team. This demonstrates the system's ability to accurately monitor waste levels in real-time, with each incremental rise in time delay showing a proportional increase in both waste level and weight.

The performance of the research model and existing models that are part of the literature study are compared and shown in **Table 5**. The performance comparison shows that the research model significantly outperformed existing models over key metrics. With an accuracy of 99.52%, it exceeds top-performing models like MCSOML-SWM (99.34%) and ResNet50V2 (98.95%). The proposed model also demonstrates exceptional precision (99.10%), recall (98.86%), and F1-score (99.38%), which are higher than those of MCSOML-SWM (97.97% precision, 97.41% recall, and 97.67% F1-score) and ResNet50V2 (98.35% precision, 93.38% recall, and 98.38% F1-score). This superior performance across all metrics underscores the model's effectiveness in accurately classifying waste with high precision and recall, marking it as a more robust and reliable solution compared to the existing models.

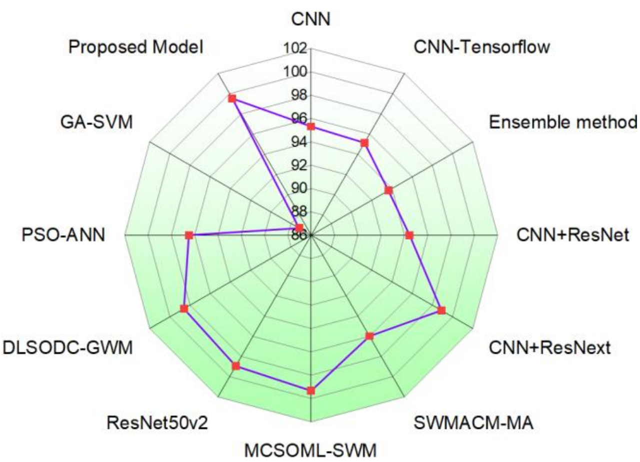


Figure 8. Graphical Representation of Accuracy Comparison

Figure 8 represents the accuracy comparison. The proposed model attains an accuracy of 99.52%, exceeding all other models evaluated. The MCSOML-SWM model attains a performance rate of 99.34%, whereas ResNet50V2 achieves 98.95%, demonstrating robust efficacy. Alternative models such as CNN+ResNeXt and DLSODC-GWM exhibit impressive performance, achieving accuracies of 98.9% and 98.61%, respectively. In contrast, earlier models like CNN and CNN-TensorFlow have lesser accuracies of approximately 95%, while conventional approaches such as GA-SVM trail with merely 87.2% accuracy. This comparison highlights the significant improvement the proposed model offers in terms of accuracy, outperforming even advanced deep learning and ensemble methods.

The graphical figure for the precision analysis comparison is shown in **Figure 9**. The performance analysis for precision shows that the proposed model outperforms other models with a precision of 99.10%, demonstrating its superior ability to accurately classify positive cases. In comparison, the MCSOML-SWM model follows closely with a precision of 97.97%, while the ResNet50V2 model achieves a strong 98.35%. Other models, such as DLSODC-GWM, exhibit a precision of 95.23%, and the PSO-ANN model records 92.2%. Models like GA-SVM and the Ensemble method lag, with precisions of 89.4% and 91.23%, respectively. This high precision of the proposed model indicates its exceptional accuracy in identifying true positive instances, minimizing false positives, and leading in classification performance compared to other models.

The graph for the recall analysis comparison is displayed in **Figure 10**. The performance study for recall indicates that the suggested model attains a recall rate of 98.86%, showcasing its superior capacity to accurately identify true positive situations, hence ranking it among the highest-performing models in this regard. The MCSOML-SWM model exhibits a recall of 97.41%, whereas ResNet50V2 attains 93.38%, demonstrating robust recall performance. Alternative models, including DLSODC-GWM and PSO-ANN, demonstrate recall rates of 92.29% and 94.2%, respectively. The GA-SVM model exhibits a recall of 85%, while the Ensemble technique demonstrates a lesser performance of 66.71%. The enhanced recall of the suggested model demonstrates its efficacy in reducing false negatives and accurately identifying the majority of positive cases, surpassing most alternative models in this essential parameter.

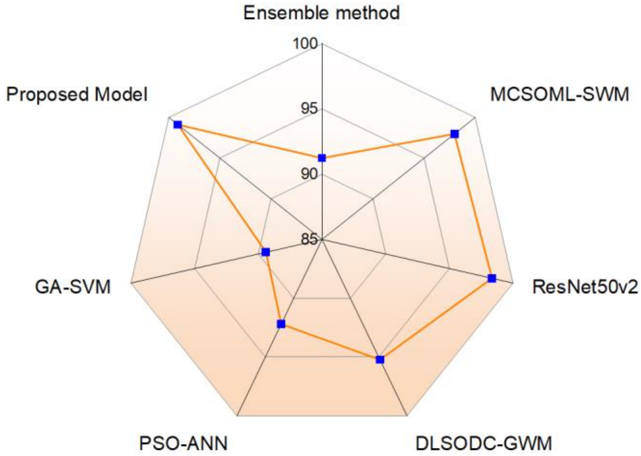


Figure 9. Graphical Representation of Precision Comparison

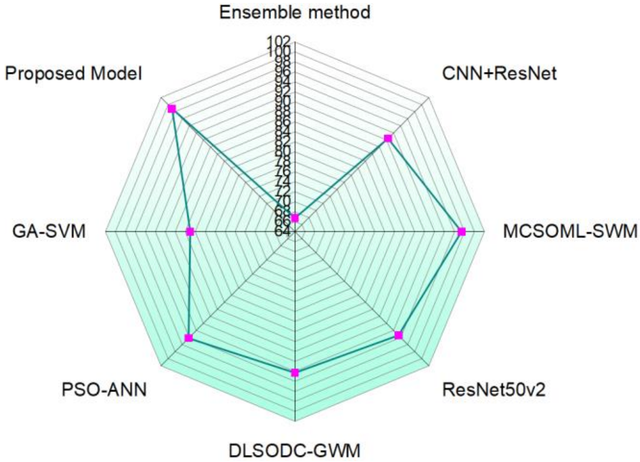


Figure 10. Graphical Plot of Recall Comparison

The graph for the F1 score analysis comparison is displayed in **Figure 11**. The proposed model attains the greatest F1-score of 99.38%, indicating superior stability between precision and recall relative to other models. The MCSOML-SWM model achieves an F1-score of 97.67%, demonstrating robust overall performance, although marginally inferior to the suggested model. ResNet50V2 achieves an F1-score of 98.38%, although it remains inferior to the proposed method. Models such as DLSODC-GWM and PSO-ANN attain commendable F1 scores of 94.72% and 92.1%, respectively, although exhibit a distinct performance disparity. CNN+ResNet and GA-SVM get scores of 92% and 89.7%, respectively, however, the Ensemble technique dramatically underperforms at 66.71%. The suggested model's F1-score demonstrates its efficacy in accurately classifying cases, surpassing all other models in this metric.

Consequently, this comparison indicates that the proposed model has achieved superior results compared to the models analyzed in this research. The developed research methodology offers several advantages compared to alternative approaches:

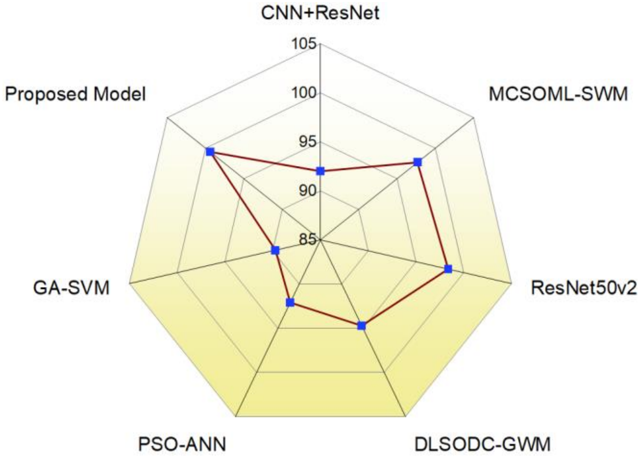


Figure 11. Graphical Plot of F1-Score Comparison

Real-Time Monitoring: The IoT-based sensors provide real-time data on waste levels, enabling dynamic decision-making and optimized waste collection.

High-Accuracy Classification: The use of the Swin Transformer V2 deep learning model ensures accurate waste classification, which is crucial for recycling and minimizing landfill use.

Optimized Routing: The integration of ACO for route optimization significantly improves the efficiency of waste collection, reducing operational costs and minimizing carbon footprint.

Scalability: The system is scalable, allowing easy adaptation to different urban environments with varying levels of waste generation and complexity.

The primary limitation of this research is that the proposed model is restricted to classifying only six categories and limited data size. In future, the data size and the waste categories can be increased.

Theoretically, the proposed research on SWM contributes to the academic field by introducing an innovative integration of Swin Transformer V2 and ACO in IoT-based waste management, setting a new benchmark for accuracy and efficiency in waste classification and route optimization. Practically, the proposed model provides a scalable and cost-effective solution for real-time waste monitoring and collection, addressing critical challenges in smart city SWM. Its application can improve resource utilization, reduce operational costs, and contribute to cleaner and more sustainable smart cities, showcasing its transformative potential in both research and practice.

5. Conclusion

The research proposed a real-time SWM model utilizing the DL methodology and an IoT-based framework developed using Swin Transformer V2. The research model includes data collection, preprocessing, selection of features and classification tasks. The TrashNet data set was collected to train and evaluate the research methodology. The data collected from IOT-based sensors are preprocessed by using a min-max scaling process. The classification of the images was performed by using Swin Transformer V2. An ACO Algorithm was employed for the Waste Collection Vehicle Routing process. In this research, the dataset is divided for training and testing, with ratios of 75% and 25%, respectively. The evaluation of the research model was conducted based on parameters including accuracy, precision, recall and f1-score. Outstanding results are also shown by the proposed framework in terms of accuracy (99.52), precision (99.10%), recall (98.86%), and F1-score (99.38%). This research categorizes waste into six types: cardboard, metal, glass, paper, plastic, and trash. These results were compared and validated with other models discussed in the literature review, and as compared, the research model outperformed all the other models. Finally, the results demonstrated that the proposed model achieved exceptional performance in terms of recall, accuracy, F1-score, and precision both during the training and testing phases, indicating its effectiveness in accurately classifying the wastes. The findings of this research present significant potential for smart cities and urban waste management systems, providing a scalable and sustainable solution for efficient waste collection, classification, and recycling. The proposed system enhances environmental sustainability by optimizing waste sorting and encouraging the reuse of materials, contributing to a clean and more sustainable urban environments. The research method can be strengthened in the future by expanding the dataset's size, adding more trash image variations in each class, and adding more waste categories to extend the coverage of observed waste.

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