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IMPROVED PARTICLE SWARM OPTIMIZATION WITH DEEP LEARNING-BASED MUNICIPAL SOLID WASTE MANAGEMENT IN SMART CITIES

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ABSTRACT

Objectives: The Internet of Things (IoT) framework is crucial for improving monitoring applications for smart cities and controlling municipal operations in real time. The most significant issue with applications to smart cities has been the handling of solid waste, which may have negative consequences on the health and well-being of people. Waste management has become a problem that developing and developed nations must face. The management of solid waste is a significant and exciting issue that affects habitats all around the world. Thus, it is necessary to create an efficient method to eliminate these issues or, at the very least, reduce them to a manageable level.

Theoretical framework: This work proposed an Improved Particle Swarm Optimization with Deep Learning-based Municipal Solid Waste Management (IPSODL-MSWM) in smart cities.

Methods: The IPSODL-MSWM approach aims to identify various types of solid waste materials and enable sustainable waste management. A Single Shot Detection (SSD) model enables efficient object detection in the IPSODL-MSWM paradigm. Then, feature vectors were generated using the MobileNetV2 model based on a deep Convolutional Neural Network (CNN). IPSO has been obtained by using a hybrid Genetic Algorithm (GA) and PSO algorithm.

Results and Conclusion: The IPSODL method has been employed for automatic hyperparameter tuning since manual trial-and-error hyperparameter tuning is time-consuming.

Implications of the research: The IPSODL-MSWM approach uses Support Vector Machine (SVM) for accurate municipal excess categorization in this work. This implies sustainable waste management model for better smart city development.

Originality/value: With an optimal accuracy of 99.45%, many simulations show the IPSODL-MSWM model's enhanced capability for classification.

Keywords: Municipal Solid Waste Management, Particle Swarm Optimization, Deep Learning, Single Shot Detection, MobileNetV2, Convolutional Neural Network, Smart Cities, Support Vector Machine.

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OTIMIZAÇÃO APRIMORADA DE ENXAME DE PARTÍCULAS COM APRENDIZAGEM PROFUNDA BASEADA NO GERENCIAMENTO DE RESÍDUOS SÓLIDOS MUNICIPAIS EM CIDADES INTELIGENTES

RESUMO

Objetivos: A estrutura da Internet das Coisas (IoT) é fundamental para aprimorar os aplicativos de monitoramento para cidades inteligentes e controlar as operações municipais em tempo real. O problema mais significativo dos aplicativos para cidades inteligentes tem sido o manuseio de resíduos sólidos, que pode ter consequências negativas para a saúde e o bem-estar das pessoas. O gerenciamento de resíduos tornou-se um problema que as nações desenvolvidas e em desenvolvimento precisam enfrentar. O gerenciamento de resíduos sólidos é uma questão importante e empolgante que afeta os habitats em todo o mundo. Portanto, é necessário criar um método eficiente para eliminar esses problemas ou, no mínimo, reduzi-los a um nível gerenciável.

Estrutura teórica: Este trabalho propôs uma otimização aprimorada de enxame de partículas com gerenciamento de resíduos sólidos municipais baseado em aprendizagem profunda (IPSODL-MSWM) em cidades inteligentes.

Métodos: A abordagem IPSODL-MSWM visa identificar vários tipos de materiais de resíduos sólidos e permitir o gerenciamento sustentável de resíduos. Um modelo SSD (Single Shot Detection) permite a detecção eficiente de objetos no paradigma IPSODL-MSWM. Em seguida, os vetores de recursos foram gerados usando o modelo MobileNetV2 com base em uma rede neural convolucional profunda (CNN). O IPSO foi obtido usando um algoritmo híbrido de algoritmo genético (GA) e algoritmo PSO.

Resultados e conclusões: O método IPSODL foi empregado para o ajuste automático de hiperparâmetros, pois o ajuste manual de hiperparâmetros por tentativa e erro consome muito tempo.

Implicações da pesquisa: A abordagem IPSODL-MSWM usa Support Vector Machine (SVM) para a categorização precisa do excesso municipal neste trabalho. Isso implica um modelo sustentável de gerenciamento de resíduos para um melhor desenvolvimento de cidades inteligentes.

Originalidade/valor: Com uma precisão ideal de 99,45%, muitas simulações mostram a capacidade aprimorada de classificação do modelo IPSODL-MSWM.

Palavras-chave: Gestão de Resíduos Sólidos Municipais, Otimização de Enxame de Partículas, Aprendizagem Profunda, Detecção de Disparo Único, MobileNetV2, Rede Neural Convolucional, Cidades Inteligentes, Máquina de Vetor de Suporte.

1 INTRODUCTION

Municipal solid waste (MSW) refers to the solid and semi-solid garbage produced in urban life daily, including waste from building and demolished structures as well as from industry, institutions, businesses, and cities (Li, J., 2021). Growing urbanization, economic expansion, and rising populations have all contributed to a considerable increase in MSW, which will reach 2.4 billion tons annually worldwide by 2025. The abundance of MSW poses a severe danger to the city's natural resources, resulting in several problems, including contamination and unlawful disposal. MSW is a significant global ecological problem, particularly in lower-income countries (Magazzino, C., 2020).

Therefore, creating effective MSWM is essential for safeguarding assets, the ecosystem, and the public's health; nevertheless, due to their complexity and diverse character, MSW environmental problems are often challenging to resolve (Ceylan, Z. 2020). Given this context, waste disposal providers have lately concentrated on enhancing MSWM and promoting the effectiveness of trash separation and reuse through cutting-edge information technology. Machine learning (ML) techniques have been effectively used in domains connected to the surroundings, such as sewage, air pollution, and MSW treatments, because of their superior capacity for modeling complicated systems.

The diversity of nonlinear connections present in the MSWM system constrains the conventional linear model. As a result, ML techniques are anticipated to be crucial in modeling, forecasting, and optimizing MSW-related problems. Information technologies utilized in building and demolition waste management services have been introduced, and several Artificial Intelligence (AI) frameworks have been used in MSWM applications based on 84 papers published between 2004 and 2019 (Ye, Z., 2020). Unlike earlier studies, this one concentrates primarily on the usage of the ML algorithm in MSWM and elaborates on it from the standpoint of the entire MSWM system.

The fields of computing, theory of probability, data analysis, approximation theory, and complicated algorithms are all included in the interdisciplinary subject of ML. The ideas and methods of ML have been successfully applied to tackle challenging issues in various sectors (Zhang, J., 2020). Data is used to "train" ML, which then utilizes a variety of algorithms to learn how to accomplish assignments. These algorithms employ records to extract hidden data that may be used for regression or categorization. Artificial Neural Networks (ANNs), SVM, naive Bayes, K-nearest neighbor, decision trees, random forests, and dynamic network fuzzy inference systems are examples of ML techniques. Since it is the most significant area of ML, DL has increased in recent years and is now a popular area for ML study (Xia, W., 2022).

Administrators should concentrate on current circumstances and plan and implement in the future following the trend in MSW generation since the equipment and infrastructure associated with the disposal of MSW frequently demand significant expenditure. Because it may help with information support for urban ecological planning, execution, and oversight, as well as the development of realistic strategies for trash gathering, transportation, and treatment, a practical forecast of MSW generation is crucial (Oguz-Ekim, P. 2021). As a result, the foundation of waste management is MSW forecasting. The MSW generation, however, is complex and influenced by various elements, including demographics, economic development, and personal choices. Nonlinear models have proven to be more accurate than linear models, and the link between factors that influence MSW formation is not purely linear (Wu, F., 2020).

Predicting trash generation and disposal rates, classifying waste during the gathering, and turning garbage into functional and recyclable materials are the treatment processes of a good MSWM. Predicting trash generation and disposal rates is the first stage in the MSW management procedure. Categorization, the second phase in the MSWm process, divides garbage into biodegradable and non-biodegradable. Sorting trash before it is picked up by sanitation personnel makes MSWM easier by turning waste into usable energy through reducing sources and recycling, feeding animals, reusing, composting, and biological processes (Fernando, R. L. S. 2019).

In today's technologically advanced culture, executing such a complicated sorting procedure manually is unfeasible. Additionally, incorrect waste categorization stems from ignorance about the origin of the trash. A technology-aided innovative waste classification framework addresses the problem of accurately classifying wastes using computer vision (Jiang, C., 2021). However, several garbage categorization models can be found in the literature, and detection accuracy still has to be enhanced. The DL models' trial-and-error hyperparameter tuning is a time-consuming operation. Consequently, automatic hyperparameter tuning may be done using metaheuristic optimization techniques. The main contributions of this paper are as follows:

- To propose an Improved Particle Swarm Optimization with Deep Learning-based Municipal Solid Waste Management (IPSODL-MSWM) in smart cities.
- To identify various types of solid waste materials and enable sustainable waste management using Single Shot Detection (SSD) model for efficient object detection in the IPSODL-MSWM paradigm.
- To generate features using the MobileNetV2 model based on a deep CNN.
- IPSO has been obtained by combining GA and PSO algorithms. The IPSODL method has been employed for automatic hyperparameter tuning and uses Support Vector Machine (SVM) for precise municipal waste categorization.

The rest of the paper has been organized as follows: Section 2 describes related research on machine learning and deep learning models for MSWM in smart cities. Section 3 provides an Improved Particle Swarm Optimization with Deep Learning-based Municipal Solid Waste Management (IPSODL-MSWM). Results and discussion have been given in section 4. Finally, the conclusion, limitations, and scope for further research have been shown in section 5.

2 THEORETICAL FRAMEWORK

Modern technologies like image recognition, IoT, and ML have become more critical in recognizing and classifying waste across various waste management areas. The most current location of active study is machine vision, where ML algorithms enable computers to comprehend and categorize digital images comparable to humans. As a subclass of ML, DL uses ANN-based feature learning to simulate the brain. A limitless number of layers comprise a DL framework, and each layer has a defined size used to accomplish real-world waste categorization applications.

The application of DL approaches and algorithms in constructing image classification models to classify waste for MSW systems was thoroughly examined by Ling et al. in their presentation from 2021 (Ling, M., 2021). The most appropriate location for Waste to Energy (WTE) facilities was also investigated in (Al-Ruzouq, R., 2022) using an Analytical Hierarchy Process (AHP)-based architecture assisted by a variety of ML algorithms (Gradient Boosted Tree (GBT), Decision Tree (DT), and SVMs). Incorporating Gaussian dispersion modeling for the anticipated air pollution emissions from a WTE facility required the development of a unique strategy.

An innovative MSWM system for a green society was presented by Dubey et al. (2020), combining IoT and ML technology (Dubey, S., 2020). Using the K-Nearest Neighbor (KNN) technique and several sensor configurations, an ML-based classification model identified and categorized the garbage. The KNN model sought to lessen pollution by correctly classifying the gathered wastes for decomposition and reuse. In addition, based on the findings of the categorization, the model notifies the user when garbage is biodegradable or not. However, because of the system's susceptibility to scaling huge datasets, KNN-based systems achieved lower testing accuracy and constrained performance measures.

An IoT-based intelligent garbage disposal monitoring and MSWM system are presented by (Ali, T., 2020). As mentioned above, this solution aids in resolving issues with managing waste and IoT-based garbage gathering for the smart city. The suggested approach effectively collects garbage, finds waste materials, and predicts future waste production. The IoT-based gadget controls and keeps an eye on the battery-powered bins. To decrease the computational difficulty of categorization, Xu et al. (2020) created a parameter prediction mechanism employing the Naive Bayes (NB) continuous learning algorithm (Xu, F., 2020).

The technological difficulties with sustainable MSWM in the context of Society 5.0 were assessed by Bui et al. Qualitative data is typically used to specify valid characteristics (Bui, T. D., 2022). To find dependable and reasonable features, the fuzzy Delphi approach is used. In a research study, ambiguous decision-making trials and assessments show how the qualities are related causally. The Choquet integral provides a general perspective of the non-additive rates over the valid set. The findings offer insight into obstacles to effective MSWM under uncertain contexts.

Through supervised ML methods, Rutqvist et al. (2019) aimed to address the issue of garbage categorization (Rutqvist, D., 2019). With sensors connected, a model has been created to categorize garbage and calculate how much rubbish has been placed within the container. To increase accuracy, an iterative data-driven strategy was adopted. A confusion matrix gauges how well the binary categorization model performs. The following list identifies the technique's research deficit. First, the iterative approach could not assess how accurately and inaccurately the waste container was detected throughout the disposal process. Second, the system uses several sensors to gauge the garbage container's capacity. Finally, the solutions' complexity is not examined or contrasted with the current solutions.

A practical, intelligent MSWM system with extra functionality to gauge and remove the trash-collecting container was demonstrated by Ahmad et al. (Ahmad, S., 2020). The datasets were subjected to qualitative and prospective data analysis techniques for efficient waste management strategy. Bin allocation for garbage collection has been done using data visualization and visual examination using Quantum Geographic Information Systems (QGIS). Hu et al. (2021) suggested a construction waste management model that classified trash into inorganic/organic, steel, composite, and potentially dangerous materials using SVM-based predictive modeling. In establishing a nonlinear connection of waste fill details and performing advanced time series prediction, forecasting data analysis failed (Hu, R., 2021).

To forecast solid waste and predict landfill space in Bangladesh with the fewest amount of input variables, Hoque et al. (2020) introduced a waste categorization model based on ANN (Hoque, M. M., 2020). A neuro-fuzzy inference system with adaptive features was used to demonstrate the effectiveness of landfill estimates compared to the ANN model. The classification method was evaluated and found to have a range of accuracy that is just marginally acceptable. Jahanbakhshi et al. (2021) created a categorization model for the carrot fruit using the CNN method. It is a straightforward method for addressing the deep neural network accuracy problem. Oriented gradient histograms and regional binary pattern techniques were employed to extract picture features, and then multi-layer perceptron, GBT, and KNN algorithms were utilized to classify the images (Jahanbakhshi, A., 2021).

Although the literature has a variety of models for categorizing garbage, detection accuracy still needs to be improved. Trial-and-error hyperparameter adjustment in the DL models takes a lot of time. As a result, metaheuristic optimization methods may be used for automated hyperparameter tuning.

3 METHODOLOGY

To allow smart MSWM, a novel IPSODL-MSWM algorithm has been developed in this work to recognize various kinds of MSW. The SSD model in the IPSODL-MSWM model enables accurate object identification. IPSO has been obtained by combining GA and PSO algorithms. The Deep CNN-based MobileNetV2 model is then used to generate feature vectors, and the IPSO technique is used to tune the hyperparameters. In this work, the IPSODL-MSWM approach used SVM for precise waste categorization.

3.1 SSD Model for Object Identification

The IPSODL-MSWM framework primarily uses the SSD model for efficient object identification. An SSD with a single and one-phase Deep CNN (DCNN) designed for real-time object detection is a single-shot multi-box detector (Kumar, A., 2020). However, the whole process runs at seven frames per second. Conversely, a novel approach in two-phase processing, the Fast Region Convolutional Neural Network (FRCNN), uses the given network to produce suggestions to identify and classify objects for immediate recognition rather than an external system. By eliminating the need for a proposal network, SSD speeds up its execution time compared to the previous detector.

Because of this, it causes minor decreases in average accuracy, which SSD makes up for by utilizing innovations involving standard boxes and multi-scale characteristics. The FRCNN may now be obtained by SSD utilizing low-quality images, speeding up SSD's processing. SSD uses a convolutional filter to recognize objects and retrieve feature maps. SSD uses MobileNetV2 as a foundation network for extracting features. To produce forecasts, it then merges six convolutional layers. Each projection includes $N + 1$ score and a limit box for each class, where N is the total number of classes, and +1 is the number of extra classes that don't have any objects. SSD uses a simpler convolutional filter in place of a Region Proposal Network (RPN) for box creation and for providing the categorizations for calculating the class ratings and object positions.

Then, for object prediction, SSD uses 3x3 convolutional filters over all cells while the MobileNetV2 base network extracts the features. Each filter output contains four characteristics for individual boundary boxes and N + 1 scores for all classes. SSD differs from other techniques because it predicts multi-scale feature maps for separate detection instead of employing a single final layer. As previously said, SSD uses low-input images for object recognition and a lower-resolution layer to detect largescale items while gradually identifying tiny things with the initial layer. SSD uses different sizes of essential boxes for intuitive presentation and layer separation.

3.2 Feature Extraction Using Deep CNN-based MobileNetV2 Model

The MobileNetV2 is intended for low-power devices with average classification capability. MobileNet is compact and uses little processing power. Adding 1x1 extension and 1x1 projection layers distinguishes the structure of the MobileNetV1 model from other models.

Table 1: Data conversion for the residual bottleneck block

Input	Operator	Output
$p \times q \times m$	1x1 pointwise conv2D, RELU6	$p \times q \times tm$
$p \times q \times tm$	3x3 depthwise conv $S = st$, RELU6	$(\frac{p}{st}) \times (\frac{q}{st}) \times tm$
$(\frac{p}{st}) \times (\frac{q}{st}) \times tm$	1x1 pointwise conv2D	$(\frac{p}{st}) \times (\frac{q}{st}) \times m$

Source: Prepared by authors (2023)

The data conversion for the residual bottleneck block is shown in Table I, where m is the dimension of the input and output channels, $p \times q$ is the dimension of the input, and st is the integer that denotes the stride. The 1×1 extension layer in the residual bottleneck block, which comprises three distinct layers, extends the input value according to the extension factor, which by convention has a value of $t = 6$.

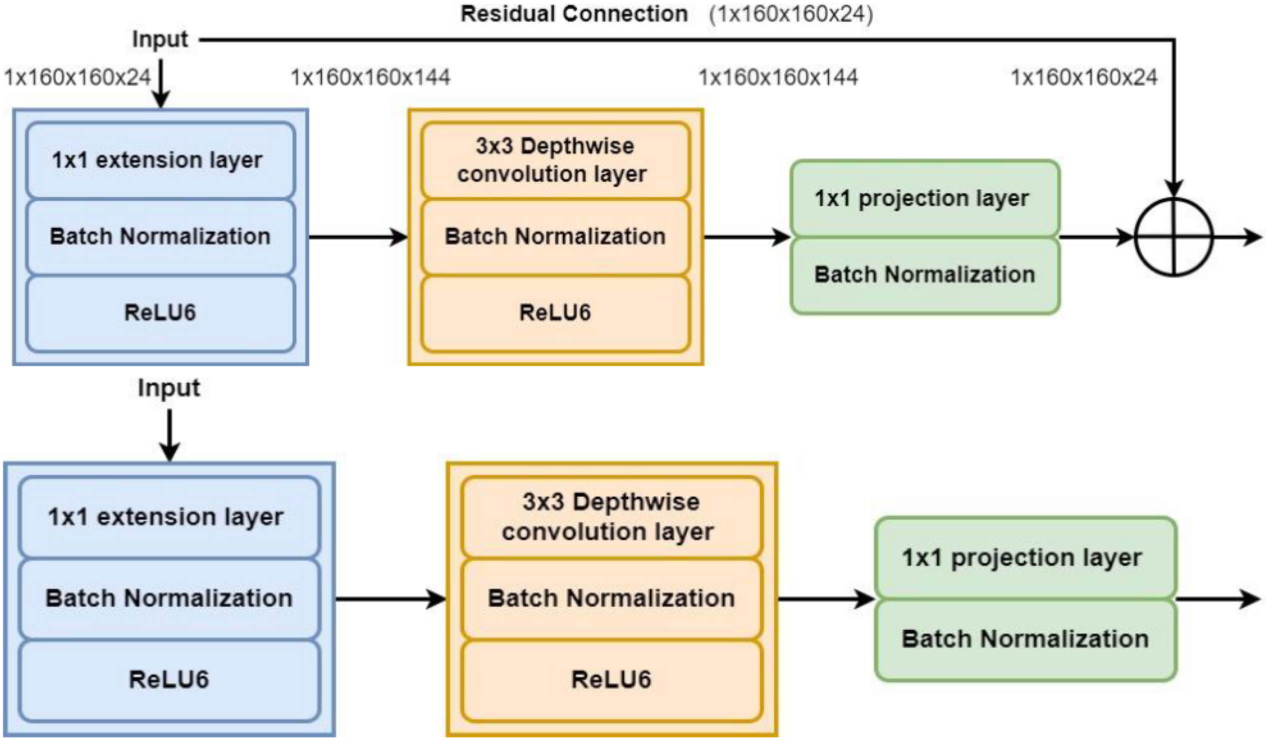

Fig. 1 Architecture of MobileNetV2 used for feature extraction
(a) Stride=1 block
(b) Stride=2 block
Source: Prepared by authors (2023)

Fig. 1 shows the architecture of MobileNetV2 used for feature extraction. In Fig. 1(a), stride equals one; in Fig. 1(b), stride equals 2. 1x160x160x24 is the input supplied to the extension layer. The extension factor is multiplied by the input channel 24 to get the output layer 1x160x160x144. The input 1x160x160x144 passed to the 1x1 Projection Layer is subjected to filters in the output sent to the 3x3 Depthwiseconv2D level. This level's bottleneck characteristic will cause the input to be decreased to 1x160x160x24. Fig. 1 shows stride=2 used to reduce the characteristics of the input data. Stride=1 is the Bottleneck residual block. The input image is processed using the MobileNet core structure for feature extraction, which is then transmitted to the SSD network, as shown in Fig. 2.

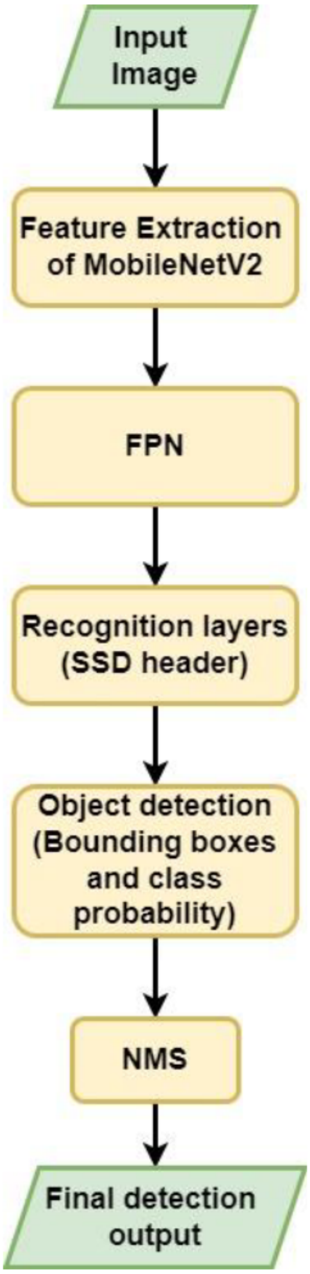

Fig. 2 SSD-MobileNetV2 architecture
Source: Prepared by authors (2023)

The SSD-MobileNetV2 architecture is shown in Fig. 2. The SSD-MobileNetV2 architecture combines the SSD and MobileNetV2 DL models. It is appropriate for use with programs like MSWM because it is made for feature extraction and object detection tasks. A flexible CNN architecture designed for situations with limited resources is called MobileNetV2. It uses depth-wise separable convolutions and flipped residuals to decrease the number of variables and calculations while retaining high accuracy. MobileNetV2 successfully strikes a compromise between effectiveness and cost, making it appropriate for applications that run in real-time on hardware with constrained processing power.

The SSD is a well-liked object detection system that effectively finds objects in images. By foreseeing object bounding boxes and the likelihood of classes at various sizes and proportions, SSD does this. The SSD-MobileNetV2 creates a compelling and precise framework for recognizing objects in MSWM applications by combining the feature extraction functions of MobileNetV2 with the object recognition abilities of SSD. Fig. 2 depicts an executive summary of the SSD-MobileNetV2 framework.

Feature Extraction: The MobileNetV2 network is in charge of extracting detailed characteristics from the input images. Its numerous convolutional layers and depth-wise separable convolutions capture various conceptualization levels. These layers analyze the source image to produce feature map representations that provide data on the existence of different image features.

Feature Pyramid Network (FPN): An FPN is used to transmit the feature maps produced by the MobileNetV2 backhaul. The FPN integrates feature maps from several dimensions to capture objects of varied dimensions. It improves how things are represented on several scales, making it possible to recognize objects accurately at various granularities.

Recognition Layers: The SSD-MobileNetV2 design adds recognition layers based on the feature pyramid. The prediction of bounding boxes and the likelihood of classes for various types of objects at multiple sizes and proportions is the responsibility of these detection layers. They employ convolutional layers with various kernel sizes to create a set of baseline bounding boxes and related class likelihoods.

Non-Maximum Suppression (NMS): An NMS technique eliminates redundant and intensely overlapping detections after forecasting the bounding boxes and the likelihood of classes. Only the most specific and non-overlapping identifications are kept as a result.

The SSD-MobileNetV2 structure provides precise and immediate object recognition in MSWM duties by fusing MobileNetV2's effective feature extraction with SSD's object detection functions. It can identify and categorize various waste products, ease garbage separation procedures, disposal, and general MSWM.

3.3 Improved Particle Swarm Optimization Using Hybrid GA-PSO

The IPSO with hybrid GA-PSO performs hyperparameter tuning since manual trial-and-error hyperparameter tuning is time-consuming. The PSO method replicates a flock of birds by creating an inert particle with only velocity and location properties. It then finds the best possible outcome by cooperating and exchanging data with the group members. The PSO starts as a collection of independent particles that each individual seeks across the solution space for the best solution. The particle evaluates its velocity for the following instant in every iteration using its present personal best (P_{best}) and present global best (G_{best}) values, and then it changes its location. The $(L+1)$ motion vector updating formula and $(L+1)$ location vector updating formula for the i^{th} particle, supposing there are j particles in the area:

$$vel_i^{L+1} = W vel_i^L + LC_1 A_1 (P_{besti}^L - P_i^L) + LC_2 A_2 (P_{besti}^L - P_i^L) \quad (1)$$

$$P_i^{L+1} = P_i^L + vel_i^{L+1} \quad (2)$$

Where,

the inertial mass factor (W) shows how the velocity of the prior iteration affects the velocity of the current iteration; the greater the value, the greater the potential of global optimization, and vice versa; A_1 and A_2 are arbitrary integers between 0 and 1, while LC_1 and LC_2 are the personal training and population training parameters, which, respectively, show the regional and global optimization capabilities.

Because each particle goes to the present ideal regional value while searching, the particles' variety rapidly decreases, making it difficult for the particles to depart from the regional optimal solution frequently. This is known as early convergence in the classic PSO method. An IPSO method is presented to address this problem by (1) using an interactive inertial weight alteration method based on the Versoria function and (2) including a dynamic mutation procedure in the iterative computation procedure (Lin, K., 2023). The Schwefel 1.2 function has been employed to verify the effectiveness of the IPSO algorithm.

The following provides more information about these two upgrades.

3.3.1 Step 1: Versoria function-based modification of the inertial mass

In the traditional PSO method, the inertial weight is constant. In contrast, prior research has demonstrated that an evolving inertial mass factor can produce better optimization results because a larger inertial weight at the start of each iteration inhibits the global search from prematurely switching to a regional optimization. A lower inertial weight should be used before the conclusion of the iterations to ensure that the algorithm converges quickly and does not veer away from the ideal solution. Although the inertial weight under this method is hardly constant, it still changes steadily, suggesting that this algorithm is just as capable as global and regional optimization but cannot find the global optimum solution. The inertial mass has been reduced using a method based on quadratic functions. Although the inertial mass constantly alters according to this approach, the inertial mass change rate in the initial phase is quicker. Then it gets shorter in the final stage, suggesting that the process may not only have inadequate effectiveness in regional optimization but may also enter a local optimum earlier than necessary.

This work employs an adaptive modification strategy based on the Versoria function for the inertial mass, which is described as follows, considering the abovementioned flaws.

$$F(y) = \frac{r^3}{r^2+y^2} \tag{3}$$

Where,

parameter r represents the radius of the function's neighboring circle; the greater the value of r, the faster the function descends from 0 to 1; and when variable r is set to 1, the function is the typical Versoria function. The parameter having r value in this study is fixed at 3, considering the overall optimization and the rate of convergence. Therefore, the formula for adjusting dynamic inertial mass is as follows:

$$W(i) = W_{max} - (W_{max} + W_{min})[\frac{16}{(\Delta_i/\Delta_{max})^2+4} - 4] \tag{4}$$

Where,

$W(i)$ is the inertial mass coefficient at i^{th} iteration, W_{max} and W_{min} are their respective highest and lowest values, which in this case are set at 0.8 and 0.3, respectively; Δ_i is the number of iterations currently being performed; and Δ_{max} is the overall number of iterations. The method has great global optimization and significant convergence effectiveness because the initial function shift rate is slow, which supports global optimization in the resulting area. In contrast, the subsequent function shift rate is quick, which supports regional search effectiveness.

3.3.2 Step 2: Dynamic mutation procedure

A hybrid Genetic Algorithm (GA)-PSO optimization algorithm has been suggested for hyperparameter tuning and validated using multidimensional evaluation issues to address the problem of a gradual decrease in the diversity of the particle population during iterative calculation (Rahman, H. F., 2019). It is based on different mixed approaches (static, flexible, alternating, and flexible mutation). In light of these findings, this work extends the PSO iteration process with a dynamic mutation operation. The likelihood of an adaptive mutation is determined as follows:

$$rand > (\frac{1}{2})(1 + \frac{\Delta_i}{\Delta_{max}}) \tag{5}$$

Where,

in equation (5), Δ_i is the number of iterations currently being performed; Δ_{max} is the overall number of iterations, and $rand$ is an arbitrary number between 0 and 1. The likelihood of particle mutation gradually diminishes as the evolutionary algebra rises; initially, the particles depart from the particle's optimization path with an estimated probability. This action successfully increases the population variety, reducing the possibility of particles finding an optimal regional solution.

The Schwefel 1.2 function (Lin, K., 2023) is used as the baseline function to evaluate IPSO's effectiveness in the current study. Due to the linked effect of its independent parameter, the gradient's path does not vary along the axis, leading to a high degree of optimization intricacy. This function's separate parameter has a range of -100 to 100. This function has an overall minimum: $F(y^*) = 0$ when y^* gets the value 0:

$$F(y) = \sum_{i=1}^{D}\left(\sum_{j=1}^{i} y_j\right)^2 \tag{6}$$

Several baseline PSO variables have been configured to be equivalent. After 500 iterations, the fitness function values of the PSO and IPSO were compared to assess their optimization effectiveness.

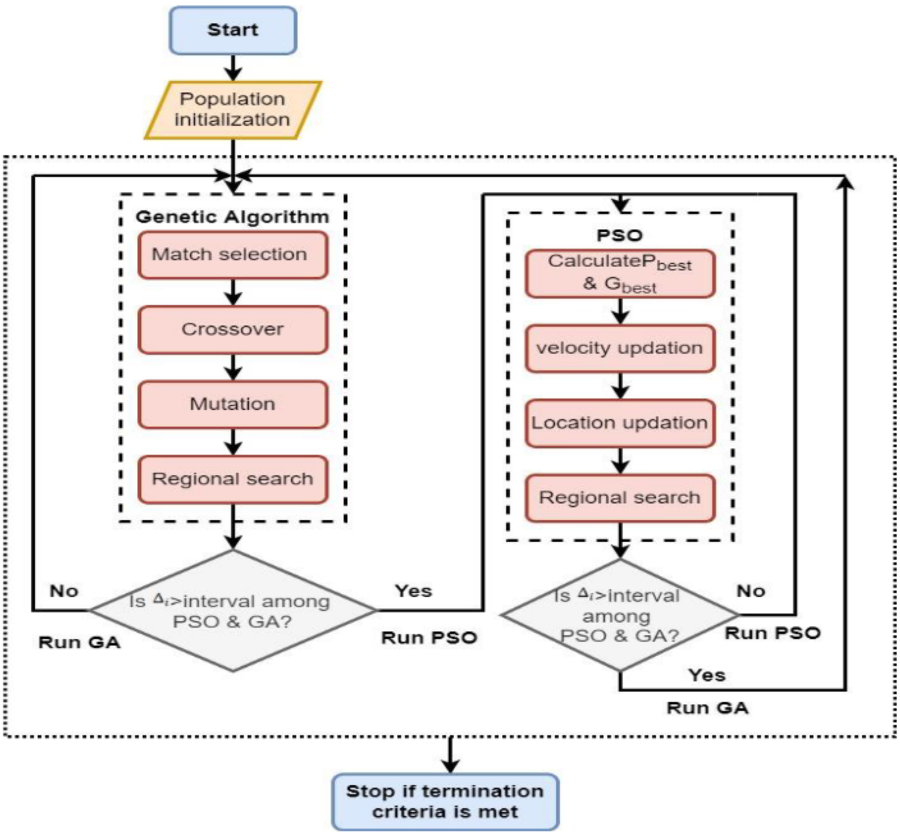

Fig. 3 Flowchart of IPSO using hybrid integration of GA-PSO
Source: Prepared by authors (2023)

Fig. 3 shows the flowchart for the IPSO algorithm through hybrid GA-PSO. Integrating GA and PSO algorithms enhances the harmony between discovery and extraction even more. Merging these two algorithms (GA-PSO) aims to combine GA's global search capability with PSO's cognitive thinking capability. The process begins by creating the original population, and then GA operations, including selection, crossover, and mutation, are carried out. To improve the GA algorithm's performance, a regional search has also been integrated. One of the factors throughout the experimental phase is the number of iterations the method has performed. After several iterations and the execution of the GA processes, the population is acquired. Starting with the produced population, the PSO algorithm randomly creates velocity for these populations, also known as swarms. A fresh set of particles (swarm) has been formed with an updated velocity, and a regional search mechanism is also integrated to enhance performance using the velocity and location update Equations (1) and (2). After a predetermined number of iterations, this process is repeated, and the optimal solution is selected depending on how well it fits the problem under consideration.

3.4 Classification of MSWM Using SVM

The MCSOML-SWM approach employed SVM for accurate waste categorization in this work. An SVM is a binary categorization where diverse real-world issues are divided into distinct groups, and the group label comprises the binary values +1 and -1. Consequently, in this work, a multiple-group SVM has been used. For 1, it has been developed a series of binary classifiers denoted by $B^1, B^2 \dots \dots B^N$. N groups have been taught to separate one particular group from the rest. By merging groups according to the most significant outcome that had previously used the sign operator $argmax\, h^k(y)$, a multigroup categorization has been accomplished.

$$h^k(y) = \sum_{i=1}^{n} x_i \propto_i^k k(y, y_i) + b^k \quad (7)$$

Where,

$k = 1,2, \dots \dots, N$. As a result, $h^k(y)$ produces signed real numbers that represent the distance between the location y and the hyperplane. Credibility values are depicted using these metrics. There is a greater degree of credibility that point y corresponds to the positive group if the values are high. Consequently, it has been ought to assign x to the group with the more excellent credibility value.

A multi-class SVM technique is frequently used to categorize waste products into multiple groups in the context of MSW classification. A good hyperplane should maximally divide different groups according to SVM, a supervised ML approach. The objective of multi-class SVM for MSW classification is to identify a choice boundary that can discriminate between different waste groups.

Choice function:

A multi-class SVM's choice function is depicted by the following:

$$CF(y) = sign(W.y + b) \quad (8)$$

y denotes the input feature vector, W is the weight vector, and b is the bias factor. The estimated group label is determined by the sign function and the $CF(y)$ computes a rating determined by the dot product of $W \; and \; y$.

Finding the best weight vector and bias term that reduces inaccurate classification while improving the difference between various groups is the goal of the SVM optimization process. This can be shown as the optimization issue as follows:

$$\min[0.5 * \|W^2\| + C * max \sum_0^1 -x_i * (W.y_i + b) \quad (9)$$

Here,

y_i is the actual group label for the sample x_i, C is the factor used for normalization that equalizes the variance and error, and the sum is computed across all training specimens. $\|W^2\|$ indicates the normalization term to regulate the intricate structure of the model. The goal is to reduce the loss function and normalization term, which impose incorrect categorization.

The IPSODL-MSWM framework's SSD model provides precise object recognition. Combining the GA and PSO algorithms yields IPSO. Next, feature vectors are produced using the Deep CNN-based MobileNetV2 model, and the hyperparameters are tuned using the IPSO method. The multi-class SVM algorithm aims to solve the optimization issue and discover the ideal weight vector and bias factor that enable precise MSW categorization into the appropriate groups and support efficient MSWM operations.

4 RESULTS AND DISCUSSION

The suggested system has been simulated using Python 3.6.5 tool on a PC with an i5 processor-8600k, GeForce 1050Ti 4 GB, 32 GB RAM, 500 GB SSD, and a 1 TB HDD. The values for the parameter contexts are: activation, ReLU; training rate = 0.01; dropout=0.5; batch size=5; epoch count=500. The TrashNet dataset has been employed in this work to evaluate the MSW classification output from the MCSOML-SWM technique (Data set,2023). The information set has been compiled and is available in this archive. The database includes six categories: garbage, glass, paper, wood, plastic, and metal. Presently, there are 2527 images in the database: 501 glass, 594 paper, 403 wood, 482 plastic, 410 metal, and 137 garbage images. The item has been positioned on a white poster board for the images, which have been taken under natural or artificial lighting. The images have been reduced in size to 512 x 384. Apple iPhone 7 Plus, iPhone 5S, and iPhone SE have been utilized gadgets.

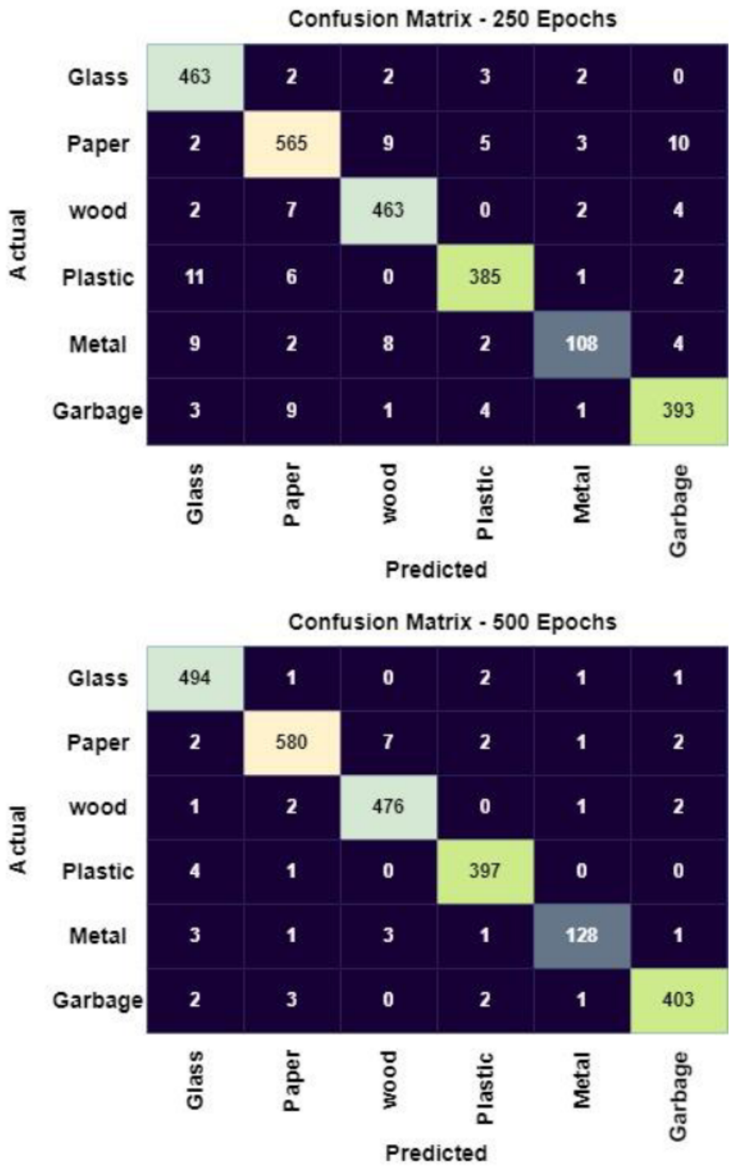

Fig. 4 Confusion matrix of the proposed IPSODL-MSWM framework
(a) Epoch=250
(b) Epoch=500
Source: Prepared by authors (2023)

Fig. 4 depicts the confusion matrix of the proposed IPSODL-MSWM framework for 250 and 500 epochs. A helpful tool for analyzing the MSW categorization model's effectiveness is the confusion matrix. It summarizes the database's true and predicted group labels (glass, paper, wood, plastic, metal, and garbage). The examples in the true class are represented in each row of the matrix, whereas the cases in the predicted class are represented in each column. The confusion matrix help to learn about the accuracy, precision, recall, and overall performance of the model. It enables computation measures like F1 score, recall, accuracy, and precision. Additionally, it aids in identifying specific faults the model produces, such as False Positives (FP) and False Negatives (FN), allowing one to comprehend the proposed framework's advantages and disadvantages and come to wise conclusions regarding MSWM application or development. The equations below illustrate how statistical measures are calculated:

Accuracy is the level of a classification model's ability to anticipate both positive and negative cases correctly. It is calculated by dividing the overall incident count by the total of True Positive (TP) and True Negative (TN) occurrences.

$$Accuracy = (TP + TN)/(TP + TN + FP + FN) \tag{10}$$

Precision is the proportion of precisely predicted positive instances among all cases expected to be positive. It assists in assessing how well the model may hinder FP.

$$Precision = (TP)/(TP + FP) \tag{11}$$

Recall, also known as sensitivity or TP rate, is the percentage of correctly predicted positive cases among all TP instances. It helps assess how well the model can identify fortunate events.

$$Recall = (TP)/(TP + FN) \tag{12}$$

The F1 score is calculated as the harmonic average of Precision and Recall. It provides a single statistic incorporating precision and recall and equally weights FP and FN.

$$F1\ score = 2 * [\frac{Precision*Recall}{Precision+Recall}] \tag{13}$$

These evaluation metrics provide valuable data on the effectiveness of the proposed IPSODL-MSWM in identifying positive and negative values in MSW categorization.

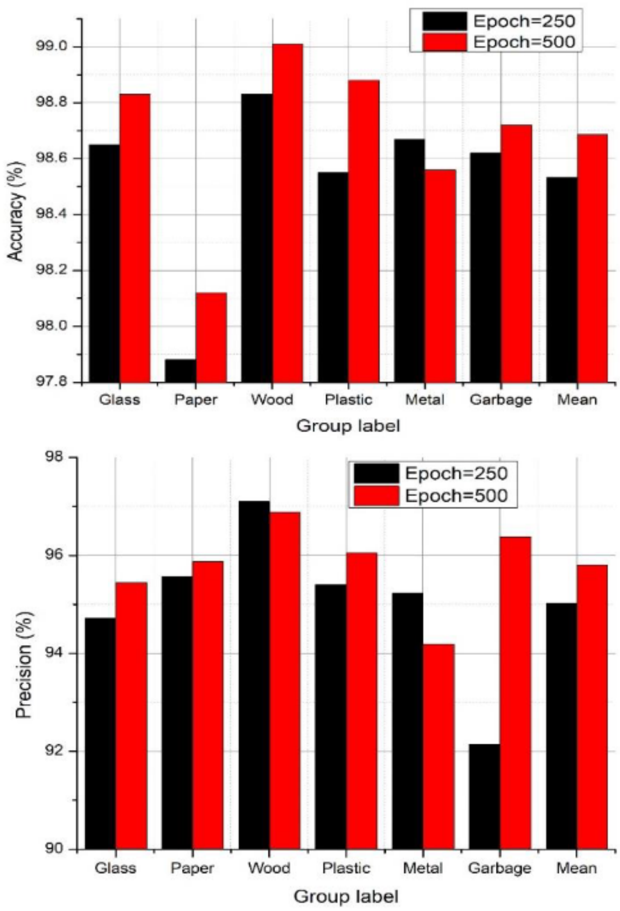

Fig. 5 Accuracy and precision (in %) for classifying group labels using the proposed IPSODL-MSWM framework with 250 and 500 epochs.
(a) Accuracy
(b) Precision
Source: Prepared by authors (2023)

Fig. 5 shows the accuracy and precision (in %) for classifying group labels using the proposed IPSODL-MSWM framework with 250 and 500 epochs. It is clear from the accuracy data in Fig. 5(a) that the IPSODL-MSWM framework achieves good accuracy percentages for epochs (250 and 500) across all group labels. For example, the accuracy varies from 97.88% (Paper) to 98.83% (Wood) during 250 epochs, showing that the model can properly categorize most examples for these group labels. With values spanning 98.12% (Paper) to 99.01% (Wood), the accuracy increases at 500 epochs, highlighting the model's ongoing improvement and improved categorization capabilities.

High precision rates have been observed from Fig. 5(b), representing the proposed framework's capacity to identify TP examples inside a certain class properly. The precision varies between 92.14% (garbage) and 97.10% (wood) at 250 epochs. For some group labels at 500 epochs, the precision values increase as the model trains. For instance, the precision for garbage rises to 96.38%, showing how the model may lessen the likelihood of making FP forecasts.

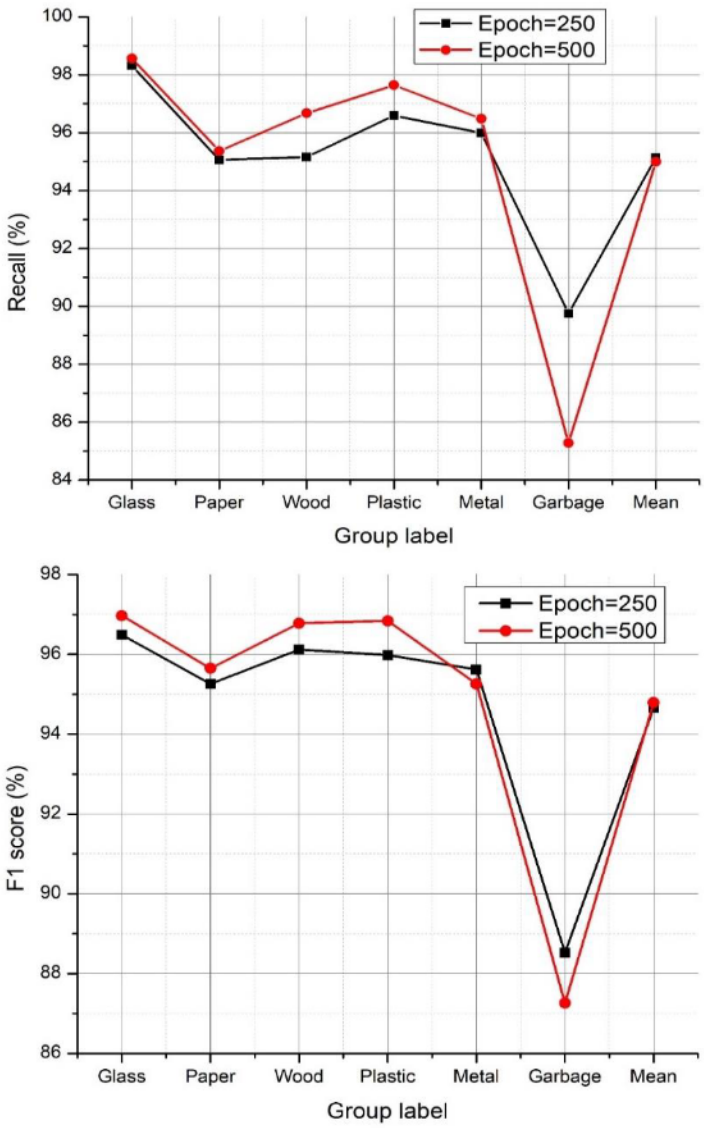

Fig. 6 Recall and F1 score (in %) for the classification of group labels using the proposed IPSODL-MSWM framework with 250 and 500 epochs.
(a) Recall
(b) F1 score
Source: Prepared by authors (2023)

Fig. 6 Recall and F1 score (in %) for the classification of group labels using the proposed IPSODL-MSWM framework with 250 and 500 epochs. Fig. 6(a) shows the fluctuations across the group labels while evaluating the recall values, which gauge the proposed framework's capacity to recognize every true case inside a group. The recall varies between 89.75% (garbage) to 98.31% (glass) at 250 epochs. Certain classes have reduced recall rates, which suggests a larger probability of FN. The recall for "garbage" is quite low (89.75% for 250 epochs), indicating that the proposed framework would have trouble accurately detecting all occurrences of garbage. Similar patterns are shown when the F1 score is examined in Fig. 6(b), which strikes a compromise between precision and recall. The F1 score at 250 epochs varies from 88.52% (Garbage) to 96.49% (Glass), showing an evenly distributed effectiveness across the various class labels.

The proposed IPSODL-MSWM framework demonstrates impressive accuracy, precision, recall, and F1 score findings, highlighting the prospects for efficient categorization of various MSW category labels. The framework continues to do well in recognizing actual cases, as seen by precision values that show strong performance over a range of MSW categories. The gains between 250 and 500 epochs imply that further training can improve accuracy, precision , and categorization abilities.

Table 2: Performance comparison of various MSWM models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 score (%)
SVM-SWM [17]	96.8	90.4	89.3	92.3
BN-CNN [21]	97	93	97	95
MSWNet [23]	97.5	93.4	94.8	95.6
MCSOML-SWM (Al Duhayyim, M. 2023)	99.01	95.82	97.31	96.97
Proposed IPSODL-MSWM framework	99.45	96.52	98.27	97.62

Source: Prepared by authors (2023)

Table 2 depicts the performance comparison of various MSWM models. The suggested IPSODL-MSWM framework significantly exceeds the performance of other models. It classifies MSW accurately and has a maximum accuracy of 99.45%. The framework correctly identifies TP, as seen by the precision value of 96.52%. The IPSODL-MSWM has the highest recall value of 98.27%.

Furthermore, the suggested IPSODL-MSWM framework is efficient, as evidenced by the F1 score of 97.62%. The IPSODL-MSWM framework regularly receives the top ratings across all measures, demonstrating its excellence in correctly identifying MSW. Although they perform admirably, the SVM-SWM, BN-CNN, and MSWNet models lag somewhat behind the IPSODL-MSWM architecture. The performance of the MCSOML-SWM model is good, especially in terms of recall and accuracy (De Paula Araújo, A. C., 2022), while the IPSODL-MSWM framework performs better in terms of precision and F1 score.

Overall, the findings indicate that the proposed IPSODL-MSWM framework outperforms the other models in terms of accuracy, precision, recall, and F1 score, indicating significant potential as an efficient and dependable solution for MSWM.

5 CONCLUSION

This research suggested an Improved Particle Swarm Optimization in smart cities with Deep Learning-based Municipal Solid Waste Management (IPSODL-MSWM) (De Souza, D. L. A., 2023). The IPSODL-MSWM technique aims to enable sustainable waste management by identifying various forms of solid waste products. In the IPSODL-MSWM paradigm, effective object detection is made possible using an SSD model (Gyamfi, N. K., 2022). The

MobileNetV2 model, based on a deep CNN, was then used to create feature vectors. A hybrid Genetic method (GA) and PSO method produced IPSO. Since human trial-and-error hyperparameter adjustment takes time, the IPSODL approach has been used for automatic hyperparameter optimization. In this study, the IPSODL-MSWM technique employs SVM to categorize MSW precisely. The suggested IPSODL-MSWM framework exhibits outstanding recall, accuracy, precision, and F1 score for effective classification of different MSW category labels. As seen by accuracy values exhibiting high performance across various MSW categories, the framework continues to perform effectively in identifying true instances. The improvements between 250 and 500 epochs suggest that more training may enhance the model's accuracy, precision, and classification capacity. The potential variability of the dataset and the lack of information from lower levels of administration, however, have been the work's shortcomings. Hybrid DL classifiers may be added to the current methodology to enhance effectiveness in the future.

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