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DCSNN OPTIMIZED WITH HYBRID BORDER COLLIE OPTIMIZATION AND ARCHIMEDES OPTIMIZATION ALGORITHMS FOR SOLID WASTE PREDICTION IN CHENNAI

The rapid growth of smart cities and industry causes an increase in waste production. The amount of municipal solid waste (MSW) increases by several factors, including population growth, economic status, and consumption trends. The inadequacy of basic trash data is a major issue for managing MSW. Numerous existing models based on solid waste prediction have been presented so far, but none of them predict solid waste accurately and also it consumes more time. To address these concerns, a deep convolutional spiking neural network for solid waste prediction (DCSNN-SWP) is proposed in this paper. Here, the real-time solid waste prediction data are gathered from the quantity of municipal corporation of Chennai (MCC), landfill, garden garbage, and coconut shell reports in Tamil Nadu (Chennai), such as Zone 9 (Nungambakkam), Zone 10 (Kodambakkam) and Zone 13 (Adyar). Then the collected solid waste data are pre-processed using the kernel correlation model. Then the pre-processing data is given to DCSNN-hybrid BCMO and Archimedes optimization algorithm which accurately predicts the solid waste as wet waste, dry waste, horticulture waste, and dumping yard for 2022–2032 years. The proposed DCSNN-SWP method has been implemented in Python.

1. INTRODUCTION

Because of the changing patterns of consumption and the growth of the urban population, solid waste management (SWM) has become a major concern [1]. Municipal solid waste (MSW) includes building and demolition debris, street sweeping, and marketable, institutional, and leftover cleaning materials [2, 3]. Together with reusable wastes like paper, plastic, glass, metal, etc., MSW also includes toxic materials like colorants,

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insect repellent, used batteries, and medications, as well as compostable living materials like fruit and vegetable peelings, leftover food, and muddy waste like blood-stained cotton, sanitary serviettes, and disposable nozzles [4]. Waste Administration Market Valuation (2007) current global MSW cohort of 2.02 billion tenors, with an annual growth rate of 8%. In India, the total number of MSWs in metropolises has increased eight times since 1947 due to cumulative growth and shifting lifestyles [5]. An estimated 90 million loads of MSW are produced annually [6, 7]. The percentage of MSW generated per capita increased to 1.33% annually [8, 9]. The type and amount of MSW generated in India varies rapidly with that of Western nations, mostly due to the appearance of hazards [10–2]. In urban areas, MSW contained a high percentage of decomposable materials (40–60%) and slow-growing (30–50%) [13–15].

The appropriate percentage of living waste in MSW was consistently increasing as socio-commercial status decreased; as a result, urban areas produce more living waste than rural homes [16–18]. The corporeal and biochemical components of MSW depend on some influences, e.g., nutritional customs, the standard of living, scale of viable events, and time of year, wherein the entire MSW cohort depends on whole inhabitants [19]. Accurate solid waste generation forecasting is essential for the efficient collection and removal of MSW. Prediction of MSW cannot be done consistently and is dependent on a variety of qualitative factors [20]. However, nowadays a great deal of study is being done regarding the prediction of solid waste. The benefits of machine learning techniques are discovered to be due to ambiguity and inadequate data obtainability [21]. Several machine learning models attempt to predict solid waste [26–32] but they achieve poor prediction accuracy, and also an increase of computation time. To handle these downsides, certain solutions are required to be put forward. These drawbacks have provoked the authors to do this study.

DCSNN-SWP is proposed for solid waste prediction in Chennai. Here, the DCSNN-SWP accurately predicts the solid waste in different zones.

The key contributions of this paper are as follows:

- DCSNN optimized with hybrid Border Collie optimization and Archimedes optimization algorithm (DCSNN-SWP) for solid waste prediction in Chennai is proposed.
- The real-time SWP data are accumulated via quantity of MCC, landfill, garden garbage, and coconut shell reports in Tamil Nadu (Chennai) such as Zone-9 (Nungambakkam), Zone 10 (Kodambakkam), Zone 13 (Adyar).
- The accumulated solid waste data are pre-processed under kernel correlation [22].
- The pre-processing data is fed to DCSNN for activating SWP with categorization [23].

Generally, DCSNN does not adopt any optimization methods to determine the optimum parameters to ensure exact SWP.

- Thus hybrid BCMO-AOA [24, 25] is employed to optimize the DCSNN, which estimates the solid waste data accurately.

• DCSNN-SWP predicts the solid waste accurately as wet, dry, horticulture, and dumping yard.

• The proposed DCSNN-SWP has been done in Python. Its efficacy is evaluated with certain performance metrics.

• The obtained results of proposed DCSNN-SWP method were compared with existing enhancing solid waste prediction with a hybrid one-dimension convolutional neural network (1D-CNN) and long short-term memory (LSTM) (1DCNN-LSTM-SWP) [27], adaptive neuro-fuzzy inference system model clustered grid partitioning with fuzzy c-means and subtractive-clustering for solid waste prediction (FCM-GP-SC-ANFIS-SWP) [29], artificial neural network and support vector machine for solid waste prediction (ANN--SVM-SWP) [30] and optimizing solid waste prediction with fuzzy information granulation and genetic algorithm-enhanced support vector regression model (FIG–GA-SVR--SWP) models [32].

2. METHODS OF PREDICTION OF SOLID WASTE VOLUME

Niu et al. [26] introduced a long-term effect detection for predicting municipal solid waste utilizing a long short-term memory (LSTM) neural network. LSTM neural network was utilized for forecasting municipal solid waste that comprises LSTM layers and dropout layers. It also considers static with dynamic features in MSW temporal variation attaining better accuracy prediction and F-Score. But it increases the computation period.

Lin et al. [27] suggested the amount of MSW estimation depending on one-dimension Convolutional Neural Network (CNN) including LSTM memory along attention mechanism: A case study of Shanghai. An attention model with one-dimensional CNN and LSTM was utilized to forecast the quantity of MSW in Shanghai. It accomplished low computation time, but more error rate.

Liu et al. [28] suggested demand gap examines MSW landfill in Beijing: in terms of MSW generation. Long- and short-term memory was combined with Grey Relational analysis to effectively forecast the formation of MSW. Originally, the grey relational analysis (GRA) was utilized to sort the manipulating characteristics of the MSW cohort to accomplish the significant manipulating index. LSTM obtains important manipulating index factors. It attained greater sensitivity and precision but increased the error rate.

Adeleke et al. [29] suggested municipal solid waste generation prediction: investigation of the impact of clustering techniques and parameters on adaptive neuro-fuzzy inference system (ANFIS) presentation. fuzzy c-means, grid-partitioning, and subtractive clustering were utilized in ANFIS model for estimating waste generation in South Africa. Socio-economic, and demographic provincial data were utilized as input variables in the 2008–2016 period, and provincial waste quantities as an output variable. It attained better accuracy and F-score. But it increases the computation period.

Ayeleru et al. [30] introduced predicting MSW amounts utilizing an artificial neural network with a supported vector machine (ANN-SVM). ANN-SVM was used to forecast the MSW amount. The prediction was dependent on historical data derived via statistics, and then the projection was made up to 2050. It reached better specificity and precision although it increased the error rate.

Liang et al. [31] suggested predicting municipal solid waste utilizing combined ANN with the Archimedes optimization algorithm including socio-economic modules. ANN optimized with Archimedes optimization, sine cosine, particle swarm optimization, and genetic algorithms for estimating monthly SW generation in Iran. It reached less computation time. But it increased the error rate.

Dai et al. [32] suggested a municipal solid waste generation distribution prediction scheme depending on the integrated fuzzy information granulation and genetic algorithm for the support vector regression modeling (FIG–GA-SVR) method. Primarily, the fuzzy information granulation was utilized to grate and forecast the three illuminating variable quantities. Kriging interpolation mode was utilized to extant the MSW generation distribution. It reached a low error rate, but a higher computation period.

3. PROPOSED METHODOLOGY

An exact prediction of solid waste in Chennai utilizing DCSNN optimized with hybrid Border Collie optimization and Archimedes optimization approach (DCSNN-SWP) is discussed in this section. The block diagram of DCSNN-SWP is given in Fig. 1. It comprises data acquisition, pre-processing, and prediction. The comprehensive explanation of every stage is specified beneath.

Data acquisition. The real-time SWP data are gathered from the quantity of MCC, landfill, garden garbage, and coconut shell reports in Tamil Nadu (Chennai) Zone 9 (Nungambakkam), Zone 10 (Kodambakkam), Zone 13 (Adyar). Then the gathered solid waste data are supplied for pre-processing for removal of redundant data.

Pre-processing utilizing kernel correlation approach. A gathered solid waste data set is pre-processed under the kernel correlation approach. This approach simplifies the large data samples along greater dimensions. This approach maintains the valuable data in the sample and also decreases the calculation. Hence, this is broadly employed in data processing. Kernel correlation can successfully predict intervals as well as correlation data analysis.

Repeated data is removed utilizing kernel correlation. Data redundancy is a vital concern in solid waste data sets. A correlation filter is determined by

$$\text{Correlation filter} = \frac{\sum_m \left(\text{Input data} \otimes \text{Filter data}^*\right)_j \otimes \text{Input data}_m^*}{\text{Input data}_m \otimes \text{Input data}_m^*} \tag{1}$$

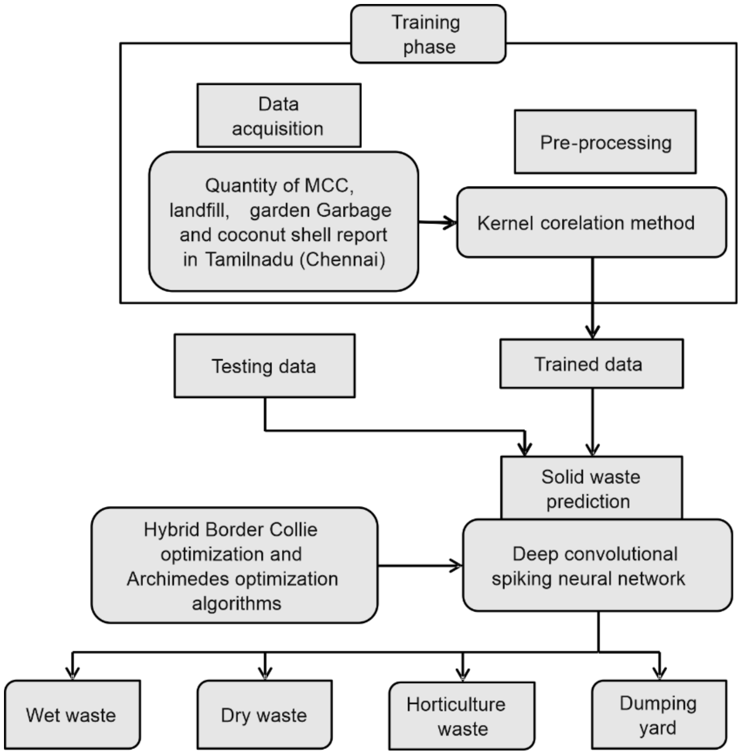

Fig. 1. Block diagram of the DCSNN-SWP method

Consider $\otimes$ the process of multiplication as multifaceted conjugation. For episodically shifted samples, the kernel correlation filter has negligible degradation and uses a quick logarithmic Fourier transform rather than matrix algebra to complete tasks quickly. For the kernel correlation filter, the error functioning requires to decrease that is considered an objective function. The error function minimization is calculated using equation

$$\min_w \sum_m \left(f\left(\text{Data sample}_m\right) = \text{Regression result of the sample}_m \right)^2 + \lambda \|\omega\|^2 \qquad (2)$$

where $\lambda \|\omega\|^2$ implies regularization expression. From this repeated data are removed in the solid waste data set. After that, the pre-processing data is supplied to the classification with prediction.

Classification and prediction using DCSNN-hybrid BCMO-AOA. The pre-processing data is supplied to the DCSNN for categorizing the data as wet waste, dry waste, horticulture waste, and dumping yard. The comprehensive illustration of DCSNN is delineated below.

The proposed DCSNN contains two states such as spike encoding and classification. These states contain several layers: a spiking encoding layer, a flattened layer, two convolutional layers, two max-pooling layers, two dropout layers, and three fully connected layers.

The pre-processed data are given to the convolution layer. The convolution layer performs the convolution process of the input matrix along a filters of $p \times q$ size. So, it presents a set of feature maps of $p \times q$ size. Since it contains Gaussian and normal, each filter learns dissimilar features. Then, max-pooling attains nonlinear down-sampling to input pre-processed data. It separates the input features into numerous non-overlapping rectangular regions. To every rectangular region, it creates output as a maximal value that supports diminishing the feature size. Max-pooling is labeled

$$y_{pqa} = \max\left\{z_{p',q'a} : p \le p' < p+s,\ q \le q' < q+s\right\} \tag{3}$$

where z implies input matrix (feature map of $p \times q$ size), y implies output matrix (feature map of $p \times q$ size), s implies padding. The pooling layer activates separately in each feature map as well as resizes it spatially utilizing max operation. This layer is introduced to manipulate with the convolutional layers limitation, i.e., to record the feature's precise position.

The concept behind dropout on neural networks is that dropout the units from visible and hidden layers. The regularization strategy is to prevent over-fitting during the training phase. This procedure decreases the complicated co-adaptations between the neurons. This is supportive of learning proficient features. The adaptation of extracted convolution features to spike trains is explained. As the classifier needs feature vectors as input, it is important to pull down the extracted features to convert the feature maps into feature vectors. In the leaky integrate-and-fire model including refractory time named soft-leaky integrate-and-fire model, the spike encode of acquired feature vectors is activated. The leaky integrate-and-fire model neuron contains 2 parts: (i) membrane potential behavior and (ii) spike-reset. The dynamics of this model neuron membrane potential $f_{\mathrm{LIFM}}(t)$ depends on input data models $s_I(t)$

$$\frac{df_{\mathrm{LIFM}}(t)}{dt} = -\frac{1}{MTC} f_{\mathrm{LIFM}}(t) + \frac{s_I(t)}{MC}, \quad t \ge 0, s_I = 1 \tag{4}$$

where MC and MTC are membrane capacitance, and membrane time stable. Normalized leaky incorporated with fire mode neuron rate response as well as refractory period are labeled in the equation

$$N = \left(t_{RP} - \tau_{MTC \times MC} \log\left(1 - \frac{1}{s_I}\right)\right)^{-1} \tag{5}$$

Assume $N = 0$, and $s_I = 1$, then the above equation can be rewritten as

$$N(s_I)=\left(t_{RP}+\tau_{MTC\times MC}\log\left(1+\frac{1}{\rho\left(s_I-1\right)}\right)\right)^{-1} \tag{6}$$

In the above equation, $\rho(j)=\max(j,0)$, $\tau_{MTC\times MC}$ means spiking neuron's membrane constant, t_{RP} is the refractory period. This maximum could be replaced with a softer maximum $\rho_1(j)=\Im\log\left(1+e^{j/\Im}\right)$. Substituting this softer maximum in the above equation, feature encoding is acquired. The solid waste classification and prediction mode are considered below.

For that, let us substitute constant input $s_I(t)=s_I$, and then determine the steady--state firing rate

$$N(s_I)=\begin{cases}\left(t_{RP}+\tau_{MTC\times MC}\log\left(1+\dfrac{1}{\rho(s_I-1)}\right)\right)^{-1} & \text{if } s_I\ge 1\\ 0 \quad \text{otherwise}\end{cases} \tag{7}$$

The proposed learning algorithm for DCSNN structure uses two-staged phases: (i) features are learned, (ii) encoded features map to specific class labels. The fundamental idea is to use a soft-leaky incorporate-with-fire model rate to encode the features, making the spiking signals differentiable so that the spiking feed-forward neural network may be trained using error backpropagation.

By this, the proposed DCSNN is learned iteratively through error backpropagation as well as cyclical learning rates on the count of epochs, wherein a single epoch is determined as an interval when every time series via the training set utilized one time. At every epoch, the training set is separated as mini-batches for batch-wise optimization. Every back propagation training phase has four segments: forward pass, backward pass, loss function, and weight updation. The feature map passes via fully connected layers till it attains the output. Then, the propagation error is examined through loss operation to generate solid waste classification output. Finally, the proposed DCSNN accurately predicts the solid waste as wet waste, dry waste, horticulture waste, and dumping yard. However, the optimum restrictions of DCSNN are required to be optimized t_{RP}, and $\tau_{MTC\times MC}$ via soft-leaky integrate-with-fire model neurons parameters to accurately predict the solid waste. The optimization approach depends on artificial intelligence and is employed in DCSNN owing to its suitability and pertinence.

Hybrid-BCMO-AOA is exploited to extend DCSNN for discovering the ideal parameters. Here hybrid-BCMO-AOA is used for tuning the weight and bias parameters of DCSNN. Generally, a certain strategy employed is constraint formation (grid, manual, and random explorations). These explorations share its unusual feebleness about reiteration time, but no subterfuge-assembled familiar search. So, to address these issues, a hybrid-BCMO-AOA is used.

Hybrid-BCMO-AOA is a metaheuristic approach. In that, BCMO mimics the sheep herding styles of Border Collie dogs and it avoids the local optima and good convergence capability. Then, the Archimedes optimization algorithm is utilized which mimics the concept of buoyant force employed mounting an object, partially or fully immersed in fluid, proportional to displaced fluid weight. It achieves a seamless changeover between exploration and exploitation and can get to the global optimum more quickly. By this, hybrid-BCMO-AOA reaches the optimized fitness solution faster. Here, hybrid-BCMO-AOA is selected because it contains its improvement; it consumes less iteration period than above mentioned explorations, and also defines better hyperparameter value.

Stepwise procedure of hybrid-BCMO-AOA for optimizing DCSNN. The step-by-step procedure is considered to get the ideal values of DCSNN based on hybrid-BCMO-AOA. First, the hybrid-BCMO-AOA makes an initial uniformly distributed population to optimize y_{pqa} and $N(s_I)$ optimum parameter values from max-pooling and steady-state firing rate of DCSNN weight with bias parameters. The optimum solution has been upgraded via hybrid-BCMO-AOA and the corresponding flowchart is represented in Fig. 2. The stepwise process is as follows:

Step 1. Initialization. The population of three dogs is initialized and sheep with their acceleration, velocity, and time from Border Collie optimization and positions of all objects with their density, volume, and acceleration from Archimedes optimization algorithm.

Step 2. Random generation. After the initialization procedure, DCSNN input parameters were generated randomly utilizing a hybrid-BCMO-AOA approach.

Step 3. Fitness function. Create the random solution from initialized values. This is examined with the parameter values optimization of y_{pqa} and $N(s_I)$ from max-pooling and steady-state firing rate of DCSNN weight and biases parameters

$$\text{Fitness function} = \text{optimization } y_{pqa} \text{ and } N(s_I) \tag{8}$$

Step 4. Position updation of dog and sheep for optimizing y_{pqa}. In this section, the Border Collie optimization approach is used to optimize y_{pqa} from max-pooling of DCSNN parameters with the position updation of dog and sheep. Initially, the velocity v of a chief, and left and right dogs are obtained using equations

$$v_C(x+1) = \left(v_C(x)^2 + 2A_C(x)P_C(x)\right)^{1/2} \tag{9}$$

$$v_L(x+1) = \left(v_L(x)^2 + 2A_L(x)P_L(x)\right)^{1/2} \tag{10}$$

$$v_R(x+1) = \left(v_R(x)^2 + 2A_C(x)P_R(x)\right)^{1/2} \tag{11}$$

where $v_i(x)$ depicts the velocity, A_i acceleration, and $P_i(x)$ position of the chief ($i = C$), left ($i = L$), and right ($i = R$) dog, respectively.

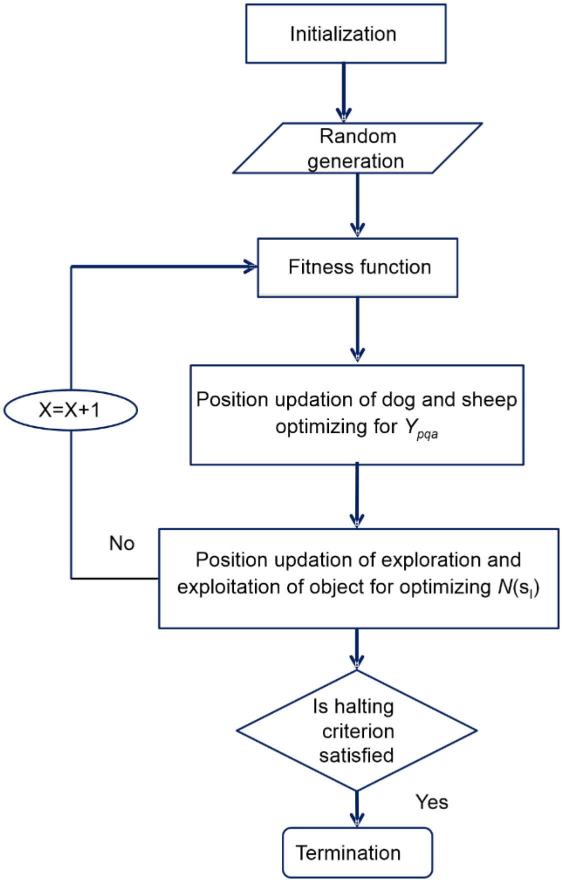

Fig. 2. Flowchart of the hybrid-BCMO-AOA algorithm for optimizing DCSNN

Then the velocity of the congregated sheep is obtained

$$v_{CS}(x+1) = \left(v_C(x+1)^2 + 2A_C(x)P_{CS}(x)\right)^{1/2} \tag{12}$$

where $P_{CS}(x)$ depicts the position of a congregated sheep. The velocity of a trailed sheep is obtained with the help of equations:

$$v_L = \left(v_L(x+1)\tan(\theta_1)^2 + 2A_L(x)P_L(x)\right)^{1/2} \tag{13}$$

$$v_R = \left(v_R(x+1)\tan(\theta_2)^2 + 2A_R(x)P_R(x)\right)^{1/2} \tag{14}$$

$$v_{TS}(x+1) = \frac{\left(v_L + v_R\right)}{2} \tag{15}$$

where θ_1 varies between 0 and 90 deg, θ_2 between 91 and 180 deg. The values of θ_1 and θ_2 are chosen randomly. Then the velocity of the observed sheep is obtained with the help of equations

$$v_{OS}(x+1) = \left(v_L(x+1)^2 - 2A_L(x)P_L(x)\right)^{1/2} \tag{16}$$

$$v_{OS}(x+1) = \left(c_R(x+1)^2 - 2A_R(x)P_R(x)\right)^{1/2} \tag{17}$$

The dog with the least fitness is considered because it is adjacent to a sheep. Then the acceleration of all dogs and all sheep (A_T) is obtained

$$A_T\,(x+1) = \frac{\left(v_T\,(x+1) - v_T\,(x)\right)}{t_T(x)} \tag{18}$$

where t_T is the negotiated total time of all dogs and all sheep:

$$t_T\,(x+1) = \text{avg}\sum_{T=1}^{k}\frac{\left(v_T\,(x+1) - v_T\,(x)\right)}{A_T\,(x+1)} \tag{19}$$

The position updations of the chief, left and right dogs are obtained by

$$P_C(x+1) = v_C(x+1)t_C(x+1) + \frac{1}{2}A_C(x+1)t_C(x+1)^2 \tag{20}$$

$$P_L(x+1) = v_L(x+1)t_L(x+1) + \frac{1}{2}A_L(x+1)t_L(x+1)^2 \tag{21}$$

$$P_R(x+1) = v_R(x+1)t_R(x+1) + \frac{1}{2}A_R(x+1)t_R(x+1)^2 \tag{22}$$

The position updation of congregated sheep P_{CS}, trailed sheep P_{TS}, and observed sheep P_{OS} are obtained with the help of the following equations

$$P_{CS}(x+1) = v_{CS}(x+1)t_{CS}(x+1) + \frac{1}{2}A_{CS}(x+1)t_{CS}(x+1)^2 \tag{23}$$

$$P_{TS}(x+1) = v_{TS}(x+1)t_{TS}(x+1) - \frac{1}{2}A_{TS}(x+1)t_{TS}(x+1)^2 \tag{24}$$

$$P_{OS}(x+1) = v_{OS}(x+1)t_{OS}(x+1) - \frac{1}{2}A_{OS}(x+1)t_{OS}(x+1)^2 \tag{25}$$

By this, it optimizes the max-pooling parameter of DCSNN with the position updation of a dog and a sheep from the Border Collie optimization algorithm.

Step 5. Position updation of exploration and exploitation of objects for optimizing $N(s_I)$. In this section, AOA is utilized to optimize $N(s_I)$. Initially, the density (D) and volume V of object l from Archimedes optimization algorithm are updated:

$$D_l(x+1) = D_l(x) + \text{random}\left(D_{\text{best}} - D_l(x)\right) \tag{26}$$

$$V_l(x+1) = V_l(x) + \text{random}\left(V_{\text{best}} - V_l(x)\right) \tag{27}$$

where D_{best} and V_{best} imply volume and density related to the best object identified so far, then random is distributed random number uniformly. Then the transference operator TO and compactness aspect CA are updated with the help of the following equations:

$$TO = \exp\left(\frac{x - x_{\max}}{x_{\max}}\right) \tag{28}$$

$$CA(x+1) = \exp\left(\frac{x_{\max} - x}{x_{\max}}\right) - \left(\frac{x}{x_{\max}}\right) \tag{29}$$

where x and $x_{\max}$ are the iteration number and maximum iterations, respectively. If $TO \leq 0.5$, the exploration phase occurs, which means there a collision occurs between the object and random material

$$A_l(x+1) = \frac{D_{RM} + V_{RM}A_{RM}}{D_l(x+1)V_l(x+1)} \tag{30}$$

where the superscripts RM and l refer to random material (RM) and object (l). Then the normalized acceleration (A_{ln}) is

$$A_{ln}(x+1) = w\frac{A_l(x+1) - \min(A)}{\max(A) - \min(A)} + r \tag{31}$$

where w and r denote the range of normalization set to 0.9 and 0.1. Then the position updation of exploration phase is obtained

$$t_l(x+1) = t_l(x) + \mathrm{Const}_1 \times \mathrm{Random} \times A_{l-\mathrm{normalize}}(x+1) \times \dim \times \left(t_{\mathrm{Random}} - t_l(x)\right) \quad (32)$$

where Const₁ equals 2, and the dimensional vector dim generates a random count among [0, 1]. Similarly, if $TO > 0.5$, the exploitation phase occurs with no collision between the object and random material

$$A_l(x+1) = \frac{\mathrm{Density}_{\mathrm{best}} + V_{\mathrm{best}} A_{\mathrm{best}}}{\mathrm{Density}_l(x+1) V_l(x+1)} \quad (33)$$

where A_{best} is the acceleration of the best object. Then update the normalized acceleration and update the direction flag using the following equation

$$DF = \begin{cases} 1 & \text{if } S \le 0.5 \\ -1 & \text{if } S > 0.5 \end{cases} \quad (34)$$

where $S = 2\times\mathrm{Random} - \mathrm{Const}_4$. Then the position updation of the exploitation phase is obtained utilizing the equation

$$t_l(x+1) = t_{\mathrm{best}}(x) + DF \times \mathrm{Const}_2 \times \mathrm{Random} \times A_{l-\mathrm{normalize}}(x+1) \times \dim\left(X \times t_{\mathrm{best}} - t_l(x)\right) \quad (35)$$

where Const_2 equals 6. X reaches the maximum and then it is directly proportional to the transference operator using $X = \mathrm{Const}_3 - TO$. By this, it optimizes the DCSNN parameters of the steady state firing rate including position updation of object exploration and exploitation phase from Archimedes optimization approach.

Step 6. Termination condition. Hyper-parameter y_{pqa} and $N(s_I)$ from max-pooling and the steady state firing rate of DCSNN weight and biases parameters optimized under hybrid-BCMO-AOA will iteratively repeat step 3 until it fulfills the halting criteria $X = X + 1$. Finally, DCSNN-hybrid BCMO-AOA estimates the solid waste generation in Chennai with better accuracy by diminishing the computational time including error.

4. RESULT AND DISCUSSION

The DCSNN optimized with hybrid-BCMO-AOA (DCSNN-SWP) for solid waste prediction in Chennai is discussed here. The proposed DCSNN-SWP technique is executed in Python. Its effectiveness is examined by certain metrics. The acquired results of DCSNN-SWP are compared to the existing models, such as evaluation of MSW quantity depending upon one-dimension CNN, long short-term memory along attention mode: a case study of Shanghai (1DCNN-LSTM-SWP) [27], municipal solid waste generation prediction: the study of clustering strategies effect and parameters on ANFIS presentation (FCM-GP-SC-ANFIS-SWP) [29], predicting municipal solid waste amount utilizing ANN with SVM: a case study of Johannesburg (ANN-SVM-SWP) [30] and municipal solid waste generation distribution prediction scheme depending on FIG–GA-SVR (FIG–GA-SVR-SWP) [32], respectively. The simulation parameter of the proposed DCSNN-SWP method is tabulated in Table 1.

Table 1

Simulation parameters

Parameter	Value
Maximum iteration	200
Velocity of dog and sheep	0–1
Time	0–1
Position	30
Dimensional vector	0–1
Normalization range *w*	0.9
Normalization range *r*	0.1
$Const_1$	2
$Const_2$	6
$Const_3$	2
$Const_4$	0.5
θ_1	0–90 deg
θ_2	91–180 deg

4.1. DATASET DESCRIPTION

The real-time SWP data are taken from the quantity of MCC, landfill, garden garbage, and coconut shell report in Tamil Nadu (Chennai) like Zone 9, 10, 13. The predicted outcome of solid waste from 2022 to 2032 around Chennai zone with the help of DCSNN--SWP technique is given in Tables 2–4.

Table 2

Predicted outcome for Corporation Chennai Zone 9, Nungambakkam under DCSNN-SWP technique [Mt]

Outcome	2022	2023	2024	2025	2026	2027
Dumping yard	509.513	524.9023	551.7277	584.3604	609.3258	615.8057
Wet waste processing	28.62	31.01693	34.05068	35.09858	39.02366	41.11426
Dry waste processing	20.5845	29.82222	36.76231	37.18362	41.78971	42.38772
Horticulture waste	15.213	18.53954	19.75569	20.15294	20.68298	22.27242
Total	573.9305	604.281	642.2963	676.7955	710.8221	721.5801
Outcome	2028	2029	2030	2031	2032	
Dumping yard	648.091	658.1658	659.8112	674.1702	683.4928	
Wet waste processing	43.26943	46.14938	48.30325	52.2567	54.95881	
Dry waste processing	42.85197	43.18789	43.67281	43.68472	46.86808	
Horticulture waste	23.94372	26.15247	27.77472	28.46363	28.83893	
Total	758.1561	773.6555	779.562	798.5752	814.1586	

Table 3

Predicted outcome for Corporation Chennai Zone 10, Kodambakkam utilizing DCSNN-SWP technique

Outcome	2022	2023	2024	2025	2026	2027
Dumping yard	524.5321	542.6516	575.5634	576.8706	582.593	592.5172
Wet waste processing	29.17619	38.98868	39.03418	41.6997	42.26803	42.36683
Dry waste processing	10.00169	10.69116	11.86208	13.79088	14.79391	15.18336
Horticulture waste	19.36887	21.95475	22.06086	23.33548	24.30765	25.20729
Total	583.0789	614.2861	648.5205	655.6967	663.9626	675.2747
Outcome	2028	2029	2030	2031	2032	
Dumping yard	593.2808	598.712	607.7993	617.9397	626.5371	
Wet waste processing	48.2589	49.03186	50.39691	51.91157	56.92565	
Dry waste processing	15.74416	15.85848	18.28591	18.36021	24.96575	
Horticulture waste	27.56571	28.67127	28.68118	29.79985	29.84155	
Total	684.8495	692.2736	705.1633	718.0113	738.27	

Table 4

Predicted outcome for Chennai Corporation Zone 13, Adyar utilizing DCSNN-SWP technique

Outcome	2022	2023	2024	2025	2026	2027
Dumping yard	429.7274	457.9681	478.4033	485.7311	488.8212	501.7036
Wet waste processing	24.6205	25.74269	27.13192	30.72409	31.9755	36.19862
Dry waste processing	3.460746	3.746106	4.861171	6.225701	7.34317	7.703916
Horticulture waste	19.65404	24.58592	26.08493	26.104	26.62033	26.88707
Total	477.4626	512.0428	536.4813	548.7849	554.7602	572.4932
Outcome	2028	2029	2030	2031	2032	
Dumping yard	510.3323	521.4036	533.3909	543.3778	549.8741	
Wet waste processing	37.88347	37.9324	38.42258	42.77969	44.59696	
Dry waste processing	9.374881	10.44931	11.11601	12.52389	12.68924	
Horticulture waste	27.23391	27.83242	28.14452	28.81033	31.17889	
Total	584.8246	597.6177	611.074	627.4917	638.3392	

4.2. PERFORMANCE METRICS

The mentioned metrics are examined to validate the performance of the proposed method. For that, the following confusion matrix is essential.

True positive (TP): accurate SWP and accurate classification.

True negative (TN): inaccurate SWP and inaccurate classification.

False positive (FP): inaccurate SWP and accurate classification.

False negative (FN): accurate SWP and inaccurate classification.

Accuracy A, precision P, specifity Sp, and sensitivity Sn, F_1 score, and error rate are given by the following equations:

$$A = \frac{TP + TN}{TP + FP + TN + FN} \tag{36}$$

$$P = \frac{TP}{TP + FP} \tag{37}$$

$$Sp = \frac{TN}{FP + TN} \tag{38}$$

$$Sn = \frac{TP}{TP + FN} \tag{39}$$

$$F_1 \text{ score} = \frac{TP}{TP + \frac{1}{2}(FP + FN)} \tag{40}$$

$$\text{Error rate} = 100 - \text{Accuracy} \tag{41}$$

4.3. SIMULATION ANALYSIS

Figures 3–10 depict the performance analysis of DCSNN-SWP and existing models. The DCSNN-SWP technique is analyzed with existing 1DCNN-LSTM-SWP [27], FCM-GP-SC-ANFIS-SWP [29], ANN-SVM-SWP [30], and FIG–GA-SVR-SWP [32] models.

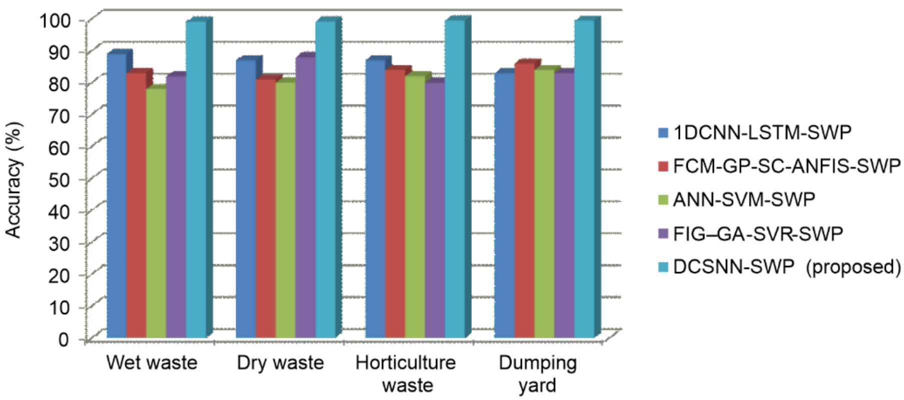

Fig. 3. Results of the predicted accuracy analysis

Figure 3 displays the predicted accuracy analysis. The DCSNN-SWP reaches greater accuracy than other methods. The ANN-SVM-SWP method attains a lesser accuracy, FIG–GA-SVR-SWP achieves a somewhat greater result with maximal accuracy value, FCM-GP-SC-ANFIS-SWP method attains a moderate accuracy value. Moreover, the 1DCNN-LSTM-SWP model reaches slightly better accuracy. The DCSNN-SWP achieves 8.93, 13.15, 26.43, and 16.96% greater accuracy for dry waste prediction, 5.73, 14.47, 20.92, and 6.74% higher accuracy for the dry waste prediction, 3.99, 7.89, 16.64, and 21.91% higher accuracy for the horticulture waste prediction, 11.73, 3.26, 7.52, and 10.01% better accuracy for the dumping yard prediction assessed to the existing 1DCNN-LSTM-SWP, FCM-GP-SC-ANFIS-SWP, ANN-SVM-SWP and FIG–GA-SVR-SWP methods, respectively.

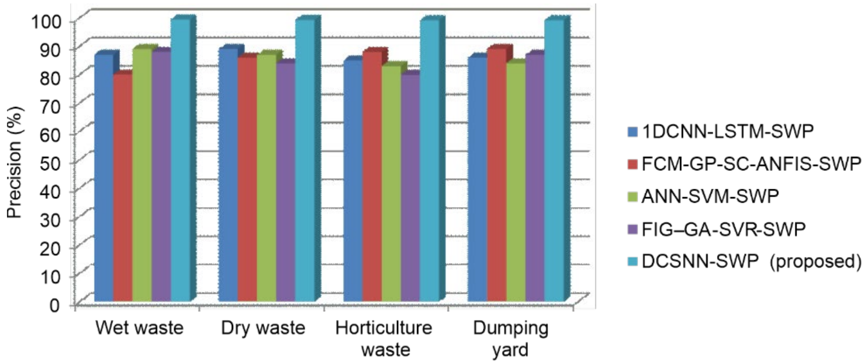

Fig. 4. Results of the predicted precision analysis

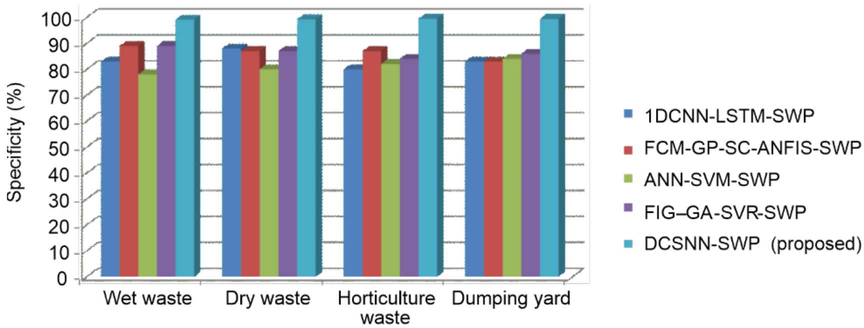

Fig. 5. Results of the predicted specificity analysis

Figure 4 shows the predicted precision analysis. Here, DCSNN-SWP method attains 8.76, 14.85, 4.44, and 11.99% higher precision for the wet waste prediction, 6.94, 15.89, 6.49, and 12.94 higher precision for the dry waste prediction, 16.68, 5.8, 9.05, and 21.01% higher precision for the horticulture waste prediction, 11.65, 3.11, 7.95 and 6.56% better precision for the dumping yard prediction than existing 1DCNN-LSTM-SWP, FCM-GP--SC-ANFIS-SWP, ANN-SVM-SWP and FIG–GA-SVR-SWP methods, respectively.

Figure 5 shows the results of the predicted specificity analysis of the existing techniques and proposed DCSNN-SWP model. The proposed DCSNN-SWP method attains 28.01, 11.14, 4.42, and 14.3% higher specificity for the wet waste prediction, 11.31, 22.77, 13.43, and 5.99% higher specificity for the dry waste prediction, 18.53, 20.86, 7.83, 12.73% greater specificity for the horticulture waste prediction, 4.8, 18.08, 10.26, and 4.62% greater specificity for the dumping yard prediction analyzed to the existing 1DCNN-LSTM-SWP, FCM-GP-SC-ANFIS-SWP, ANN-SVM-SWP and FIG–GA--SVR-SWP methods.

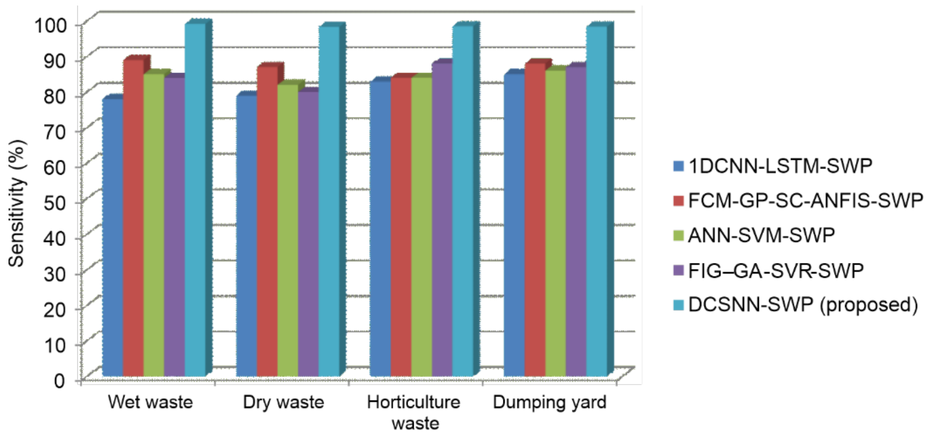

Fig. 6. Results of the predicted sensitivity analysis

Figure 6 shows the results of the predicted sensitivity analysis of the existing techniques and proposed DCSNN-SWP model. The proposed DCSNN-SWP method attains 25.39, 7.34, 13.37, and 14.39 higher sensitivity for the wet waste prediction, 25.61, 7.69, 11.81, and 20.62% higher sensitivity for dry waste prediction, 18.92, 6.44, 9.23, and 5.01% greater sensitivity for the horticulture waste prediction, 17.73, 2.01, 9.58, and 7.006% greater sensitivity for the dumping yard prediction assessed to the existing 1DCNN-LSTM-SWP, FCM-GP-SC-ANFIS-SWP, ANN-SVM-SWP, and FIG–GA-SVR-SWP methods, respectively.

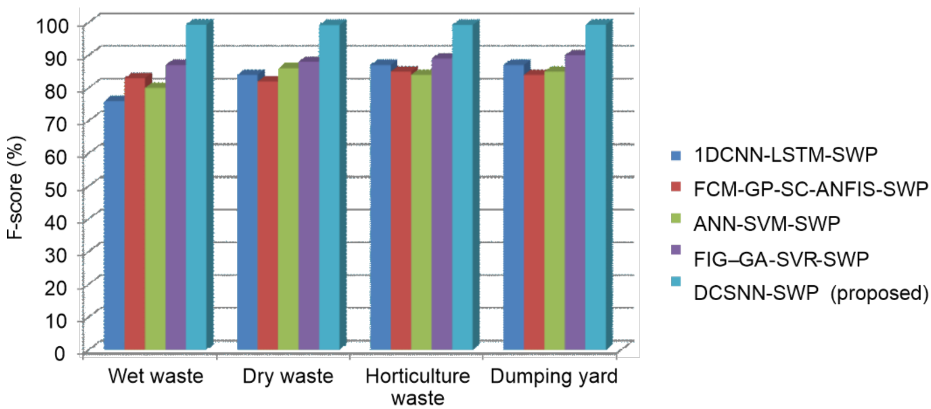

Fig. 7. Results of the predicted *F*-score analysis

Figure 7 implicates predicted F-Score analysis. Here, DCSNN-SWP method attains 29.35, 15.71, 20.79%, and 10.63% higher F-Score for wet waste prediction, 17.55, 14.63, 20.29, and 9.299% greater F-Score for dry waste prediction, 16.45, 12.3, 19.52, and 8.53% greater F-Score for horticulture waste prediction, 11.46, 6.18, 18.48, and 7.65% greater F-Score for dumping yard prediction analyzed with existing 1DCNN-LSTM-SWP, FCM-GP-SC-ANFIS-SWP, ANN-SVM-SWP and FIG–GA-SVR-SWP methods, respectively.

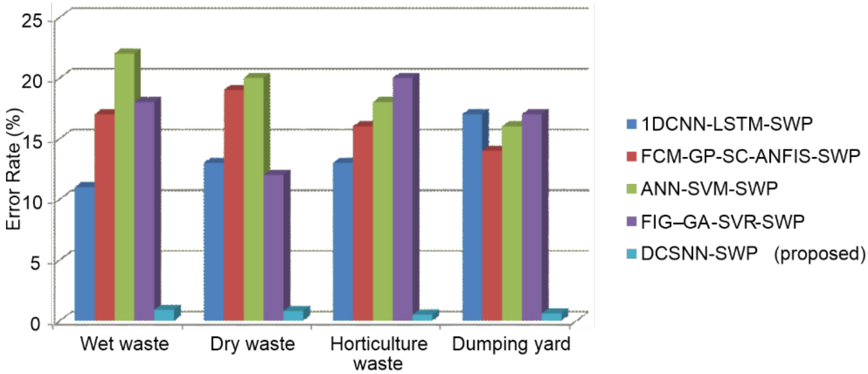

Fig. 8. Results of the predicted error rate analysis

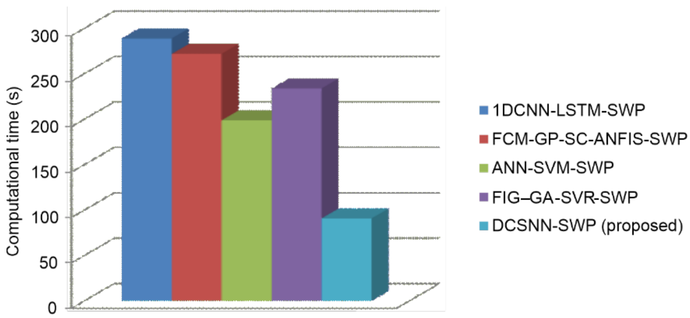

Fig. 9. Results of the predicted computation time analysis

Figure 8 represents the results of the predicted error rate analysis. The DCSNN-SWP reaches 98.43, 98.88, 99.37, and 99.10% less error rate for the wet waste prediction, 85.82, 93.38, 95.09, and 87.59% less error rate for the dry waste prediction, 84.19, 91.02, 95.18, and 96.13% less error rate for the horticulture waste prediction; 91.87, 77.3, 88.27, and 90.73% less error rate for the dumping yard prediction analyzed to the existing 1DCNN-LSTM-SWP, FCM-GP-SC-ANFIS-SWP, ANN-SVM-SWP and FIG–GA-SVR-SWP methods.

Figure 9 displays the results of the predicted computation time analysis of the existing techniques and proposed DCSNN-SWP model. The proposed DCSNN-SWP method attains 69.58, 64.91, 53.96, and 64.48% lower computation time compared with those offered by the existing 1DCNN-LSTM-SWP, FCM-GP-SC-ANFIS-SWP, ANN-SVM-SWP and FIG–GA-SVR-SWP methods, respectively.

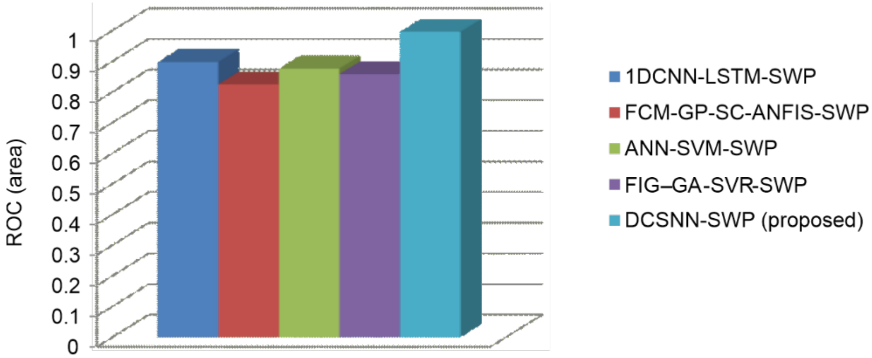

Fig. 10. Results of the receiver operating characteristics (ROC) analysis

Figure 10 shows the results of the ROC analysis of the existing techniques and proposed DCSNN-SWP model. The proposed DCSNN-SWP method attains 5.35, 3.97, 2.688, and 2.265% higher area under the curve (AUC) compared with THE existing 1DCNN-LSTM-SWP, FCM-GP-SC-ANFIS-SWP, ANN-SVM-SWP, and FIG–GA-SVR-SWP methods, respectively.

5. CONCLUSION

Deep convolutional spiking neural network for solid waste prediction (DCSNN-SWP) is implemented successfully for SWP in Chennai. The DCSNN-SWP technique is done in Python, its efficacy is analyzed with mentioned metrics. The DCSNN-SWP achieves 11.01, 9.91, 6.98, and 13.13% higher precision, 15.66, 18.22, 8.98, and 9.414% higher specificity, 21.91, 5.87, 11, and 11.75% higher sensitivity, 18.7, 12.21, 19.77, and 9.03% higher F-Score and 90.08, 90.15, 94.48, and 93.39% lower error rate compared with existing 1DCNN-LSTM-SWP, FCM-GP-SC-ANFIS-SWP, ANN-SVM-SWP and FIG–GA-SVR-SWP methods, respectively. Regardless of origin, hazard potential, or content, these waste types must be dealt with thoroughly to ensure optimal environmental run-throughs. Since waste management is a crucial component of maintaining natural cleanliness, it should be included in ecological planning. The primary objective of waste management is to prevent and eliminate harmful effects of waste materials on the environment and human health to preserve economic growth and higher standards of living. The proper disposal of unneeded items requires a lot of human resources and should be done in the most efficient way possible by preventing the growth of trash and controlling costs. So in the future, an Internet of Things-based waste management system utilizing the proposed technique will be used.

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