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BSO-CNN: A BSO Pressure Optimized CNN Model for Water Distribution Networks

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Abstract: Urban water distribution networks must use pressure management to reduce water leakage by modifying storage tank pressure levels in response to variations in water demand. Since each demand node usually restricts the maximum pressure that may be applied, addressing pressure issues at individual nodes is also crucial. To overcome these difficulties, a brand-new Convolutional Neural Network (CNN) Pressure Optimization Model is proposed. This model collects real-time data on water levels and pressure by utilizing level and pressure sensors, and a Backtracking Search Optimization (BSO) model is used to process the data. Subsequently, the optimized data is employed to execute accurate flow control protocols and detect possible leakage points. Major advantages are achieved with the BSO-CNN approach, including lower operating costs, more efficiency, and less water pressure needed. Furthermore, the model demonstrates a noteworthy decline in leakage rates, attaining a noteworthy reduction of roughly 31.5 % in the water distribution network. Improving the sustainability and performance of urban water distribution systems can be achieved through the proper integration of predictive modeling and advanced optimization techniques.

Keywords: Backtracking Search Optimization Algorithm (BSO); Convolution Neural Network (CNN); hydraulic reliability; leakage; pressure management; storage tank; Water Distribution Networks (WDN)

1 INTRODUCTION

An essential and renewable resource for maintaining life on Earth is water. It is of the utmost importance and a basic requirement for human existence [1, 2]. Water delivery firms provide one of the most basic necessities of modern life by facilitating the distribution of water to enterprises, industrialized communities, and metropolitan centers. Water delivery firms operate within a complete water supply system that includes multiple stages, including the procurement, treatment, and distribution of water to final users [3]. These systems are carefully planned and operated to guarantee a steady and dependable supply of clean water to fulfill the various demands of the community [4].

Pumping stations are essential to the operation of water supply systems because they keep the water pressure constant across the distribution network [5]. These stations pressurize the water network using sophisticated processes, frequently depending on raised reservoirs or storage tanks to enable effective distribution [6]. Water delivery companies, along with the infrastructure they support, such as pumping stations, are essential to contemporary civilization because they guarantee the availability of clean, drinkable water, which is necessary for the survival of enterprises, industries, and communities [7]. Water Distribution Networks (WDNs) are an integral part of industrialized societies' infrastructure, carrying out the crucial task of effectively transporting water to locations of consumption while preserving proper pressure and velocity levels [8]. WDNs are intricate networks made up of reservoirs, consumption nodes (many households, businesses, and industries), and a complex web of pipelines that connects these nodes. Ensuring the safety and dependability of the water supply is important to WDN operations [9]. This means that in addition to supplying water at the places of use, sufficient pressure levels must be maintained to enable its effective distribution. But WDNs face many difficulties, chief among them being energy consumption and water leakage [10]. For WDNs, water leakage is a major concern, typically accounting for 25 % to 30 % of the total amount of water provided. This inefficiency contributes to financial losses, negative environmental effects, and the loss of a valuable resource [11]. Furthermore, a large amount of WDN operating costs are related to energy usage, which emphasizes the need for efficiency gains. WDNs' scope and complexity are growing along with the population and size of metropolitan regions [12]. This increase highlights how crucial it is to have the best possible design, operation, and rehabilitation procedures in place to guarantee that customers receive satisfactory services. Strategic planning and management are crucial to successfully address difficulties and improve the resilience and sustainability of water supply systems in the face of changing urban landscapes and increasing demands, given the huge extent and complexity of WDNs [13].

Water loss is an inherent difficulty in almost all Water Distribution Systems (WDS), regardless of their age or design. The kind and amount of these losses varies based on a number of factors [14]. Water loss may be regarded as inevitable to some degree, but proactive steps can be done to lessen its effects and lower related expenses. Administrators are now concentrating on creating leakage management models to achieve the greatest possible reduction in leaks at the lowest possible cost as a result of efforts to address water loss [15]. This goal has sparked a lot of research projects that try to come up with novel tactics and tools to stop water leaks [16]. The adjustable pressure in the network pipes is one important factor that greatly affects the amount of leakage in a WDS. Water leakage, electricity consumption, and the general safety and dependability of the water supply are all significantly impacted by the pressure levels in the Water Distribution Network (WDN). Operators can minimize the amount of water loss by carefully controlling and regulating the pressure inside the network, which improves the system's sustainability and efficiency [17].

In this regard, decreasing pressure alone or in conjunction with other approaches is a feasible, practical, and cost-efficient strategy for leakage management [18]. This force reduction is required to provide the sufficient pressure to satisfy the consumers demand throughout the day and night. Using Pressure Relief Valves in the WDS is one strategy for reducing excess pressure in the network. The installation of Pressure Reducing Valves in a WDS might be viewed as an optimization challenge. However, in order to minimize leakage, optimization methods can be employed to find the optimum number, placement, and settings of the valves [19], so if the pressure is excessive, the structure suffers with several catastrophic water leaks, enhanced energy usage, or even uncontrollable cylinder rupture rates. Owing to the difficulty of enormous WDNs as well as the time-varying features of water needs, universal management is essential to accomplish pressure management. The statistical properties of the research is given in Tab. 1.

Table 1 Statistical properties

Statistical properies	Value
Skewness	0.32
Coefficient of variation	0.15
Confidence Interval	[0.28, 0.36]
Distribution Characteristics	Normal
Minimum	10.4
Maximum	25.6
Median	18.2

The objective of this investigation is to create a pressure model which minimises system leakage while taking system robustness and difficulty in meeting demand into account by estimating hourly levels of water in storage facilities for four alternative seasonal usage methods. A BSA-based optimization approach was used for this objective. The paper's important focus is the development of a water level fluctuation mechanism in the water tank to prevent leakage.

The article is arranged as : Section 2 explores the literature on pressure optimization in WDNs. Section 3 describes a Novel Neural Network Based Pressure Optimization Model. Section 4 delves into the empirical results, comparisons, and analyses. Section 5 brings the paper to a close.

2 LITERATURE SURVEY

Much research on the pressure optimization of WDNs has been published. Several proposed solutions, such as the two-phase system in [20], are founded on the design and improvement of devices that lower pressure. Since adding pressure-lowering valves to existing WDNs is challenging, more effort is being focused on improving the control of existing WDN elements in order to maximize pressure.

Jafari-Asl et al. [21] are investigating the best pressure control for reducing leakage in water supply networks. In order to solve these problems, an optimisation strategy centred on a recently developed method called Cultural Algorithm (CA) was introduced. However, this technology for locating pressure-reducing valves and making an effort to regulate them decreased the system's average leakage rate by 10 % in the third top eras.

Mehdi et al. [22] employed a distinct VSI index and enhanced the NPRI index to create a novel, step-by-step method for determining the ideal state and arrangement of PRVs in the WDN. The PSO algorithm was employed in this method, and the outcomes demonstrate how effective it is to change nodal pressures with reduced leakage rates by strategically placing PRVs in WDN.

An inventive optimization technique called the Whale Optimization Algorithm (WOA) is utilized to build pipe networks as cheaply as possible by Riham et al. [23]. It employs a performance indicator based on generations and evaluations and spherical search agents to handle discontinuity in pipe sizes. WOA was found to be more cost-effective when compared to other optimization approaches in the study. For faster convergence, more investigation is required.

Manolis et al. [24] suggested using a unique heuristic technique to create the best looping Water Distribution Network (WDN). The foundation of this approach is choosing the best watercourses to include in a WDN. The new method does not need the use of a penalty function or the modification of any parameters. The optimization approach is driven by two distinct subroutines that undertake search space exploration and exploitation by attempting sequentially and globally targeted decreases in network pipe widths.

Sitzenfrei et al. [25] created a unique edge betweenness centrality (EBCQ)-based design technique for the Water Distribution network study using CNA (Complex Network study). Determining how successfully CNA could be used as a stand-in for pressure assessment in the absence of hydraulic models is the aim of this optimization technique. Consequently, a detailed analysis of the different weight improvements is conducted, along with an evaluation of the impact on pressure predictions.

Salcedo et al. [26] presented a methodology for efficient WDN synthesis using disjunctive probabilistic Mixed-Integer Nonlinear Programming (MINLP) that accounts for linked uncertainty in nodal requests. This research used approaches for removing nonconvex nonlinearities in equations to eliminate unnecessary complexity. The impact of various covariance matrices is investigated in order to understand how the system handles uncertainty. A case study was created in order to evaluate the concept and development suggestions. The results show that when uncertainty is present, the overall stochastic solution of WDN outperforms the predictable one, suggesting that ignoring uncertainty in the optimization problem could lead to a suboptimal or, in the worst case, unrealistic WDN design.

Diego et al. [27] suggested a strategy to produce near-optimal Pareto fronts (PFs) by combining domain information from energy-based methodologies with a genetic computation to increase convergence rate and lower overall processing needs. This method is broken down into three steps: pre-processing the data from the Optimal Power Usage Surface (OPUS), parametric calibration, and regular feedback in NSGA II utilizing OPUS. This method was tested in four benchmark systems with different features in order to reduce WDN costs while increasing reliability. The results showed that the feedback system increases the effectiveness of the system, particularly during the first period of use.

Cassiolato et al. [28] proposed a precise mathematical programming method to reduce the cost of looping WDN while accounting for a discrete range of commercial sizes and the pipe lengths that are provided.

Mehzad et al. [29] optimized pump scheduling by taking three objective characteristics into account. Water velocity in the pipes and nodal pressures determine hydraulic reliability. On the other hand, we designed a three-objective optimization approach named Clustered Non-dominated Archiving Ant Colony Optimization (Clustered-NA-ACO) and assessed its efficacy using DTLZ test functions because the quality dependability at consumption nodes depends on water age.

Zhang et al. [30] offered a water supply strategy that combines the regulatory and financial cost functions via a weighting function to solve the procedure optimization problem. It also linked the price of threats with the controllable pressure based on customer dispersion. Conditions that are right can guarantee closed-loop stability. These approaches work well at different risk levels, which is essential for WDN operation.

However, in various current works, there will be limits such as it requires more cost even if it decreases the cost, they did not concentrate on other characteristics such as leakage, energy. To take into account all of the constraints, a new pressure control model must be constructed.

3 NEURAL NETWORK-BASED PRESSURE OPTIMIZATION MODEL

The operational costs of water distribution networks (WDNs) are directly impacted by variations in consumer demand. It is crucial to make the best use of available water resources in order to reduce these expenses. In this context, dynamic operational optimization strategies—including efficient pressure management—are essential. Nevertheless, despite its significance, there is a conspicuous lack of study on pressure management strategies designed to deal with water scarcity problems. After identifying this gap, it is necessary to formulate appropriate optimization objectives and control strategies. To ensure effective WDN operation in the face of water scarcity concerns, these factors must be addressed. To address this requirement, a novel neural network-based pressure optimization model for WDN water pressure regulation has been developed. The objective of this model is to optimize pressure management in order to improve operational efficiency and lessen the negative impact of water scarcity on WDNs. To begin, a Backtracking Search Optimization (BSO)-based approach is utilised to estimate the seasonal changes in a holding tank in order to prevent leaks. In the proposed study, the outcomes of a water distribution simulation study are consumed to train a CNN system. Lastly, the CNN model's output as a water pressure function is connected with BSO-based optimisation problem to adjust water pressure and leakage at every node of the water distribution network depending on storage tank water level, water usage, and node elevation. Fig. 1 depicts the proposed work's architecture.

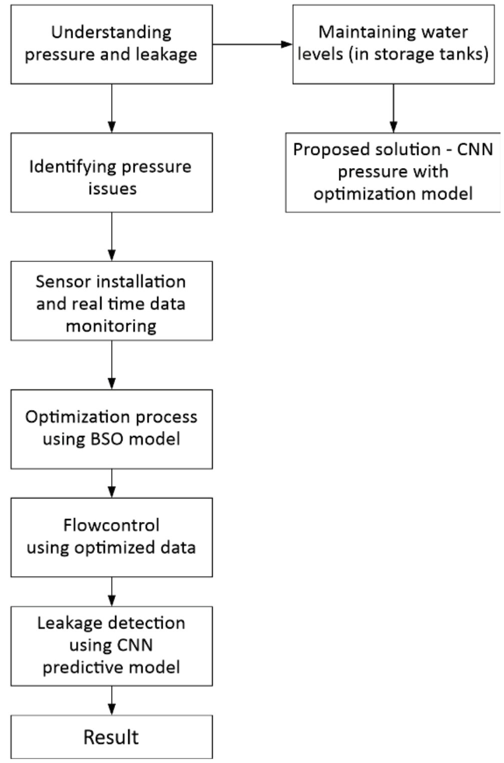

Figure 1 Structure of the proposed model

3.1 Backtracing Search Optimization BSO Algorithm based Pressure Management

Pipes, pumps, tanks, and valves comprise a system for distributing water. Each of these elements fail, but because to the great amount of pipes in water supply system, pipe leakage is far more common. Because leakage is strongly related to pressure, a pressure control system might be devised to reduce leakage. Consequently, in this work, the Backtracking optimization approach is utilised to calculate the ideal water value levels in the holding tank. BSAs are adaptive approaches that can be successfully applied to optimization issues. BSAs are most commonly used to solve issues with a significant level of complexity, non-linear behaviour, with a great amount of decision variables. The existing BSA models are modified and made compatible for our application of WDS. In Fig. 2 the water distribution system is organized as follows.

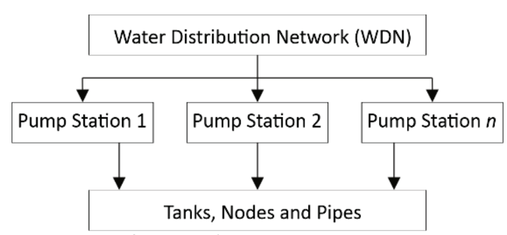

Figure 2 Structure of the water distribution networks

It is required to create a framework that could mirror the interaction among the controllable variable in the actuator as well as the controlled variable. Every constituent's pressure-flow relationship is examined. For tanks, the mass balance interaction connecting the storage capacity f in the j^{th} tank is stated as

$$f_j(d_t+1) = f_j(d_t) + \Delta d_t \left(\sum_z b_{z,j}^{in}(d_t) - \sum_m b_{j,m}^{out}(d_t)\right) \tag{1}$$

where Δd_t signifies the sampling time and d represents the discrete-time instant. The inflow from the z^{th} element to the j^{th} tank is denoted by $b_{z,j}^{in}$, while the outflow from the j^{th} tank to the m^{th} element is denoted by $b_{j,m}^{out}$. The pressure supplied by the j^{th} tank is expressed in a_j, that incorporates the j^{th} tank's elevation and water level. The pressure a_j is then calculated as follows:

$$a_j(d) = \frac{f_j(d_t)}{C_j} + U_j \tag{2}$$

where C_j is j^{th} tank's cross-sectional area and U_j is the j^{th} tank's elevation. Flow is denoted as b, whereas pressure is denoted as a in the following equations. The definition rules for b and a subscripts are the same as for $b_{z,j}^{in}(d)$, $a_j(d)$. The formulation for mass conservation in the l^{th} node for nodes is

$$\sum_z b_{z,l}^{in}(d) = \sum_m b_{l,m}^{out}(d) \tag{3}$$

The inflow might be controlled by pump stations or uncontrolled by tanks or other networks. The outflow is not ever tampered with. The Hazen-Williams equation is used to define the pressure-flow relationship in pipes. A pipe connection could be categorized as follows:

$$a_z(d) - a_m(d) = \frac{10.67 N_{z,m}}{S_{z,m}^{1.852} T_{z,m}^{4.87}} b_{z,m} \left|b_{z,m}\right|^{0.852} \tag{4}$$

where $N_{z,m}$, $T_{z,m}$, and $S_{z,m}$ are the length, diameter, then roughness coefficient of the pipe, separately. Pump stations generate network pressure; flows thru the pump stations are also controlled variables. Water usage by consumers in a certain geographical region is represented by the water usage sectors. In this research, short-term consumption forecasts are used, which can be derived using appropriate forecasting techniques.

In the WDN concept, tank pressures constitute the state variable vector $\boldsymbol{g}$, while flow-through pump units create the control input vector $\boldsymbol{e}$. The non-controlled input vector $\boldsymbol{k}$ comprises all non-manipulated flow via the pipes, the pressures at nodes linking to the water usage sectors create the controlled output sequence h, while all additional pressures make up the non-controlled output sequence i. The water-consuming vector $\boldsymbol{t}$ is formed by the spent water from all water consumption sectors. e_1 reflects movement of pump stations linked to the tank, while e_2 represents the movement of everyone else. The system's cumulative weight balance is expressed as shown on Fig. 3.

The dynamic model (tank model) could be stated using Eqs. (1), (2), and (5) as where P, Q_1 and Q_2 are system matrices of appropriate size. Eqs. (2), (4), and (5) could be used to describe the model's dynamic component. Ehere $v(.)$ and $x(.)$ are nonlinear functions.

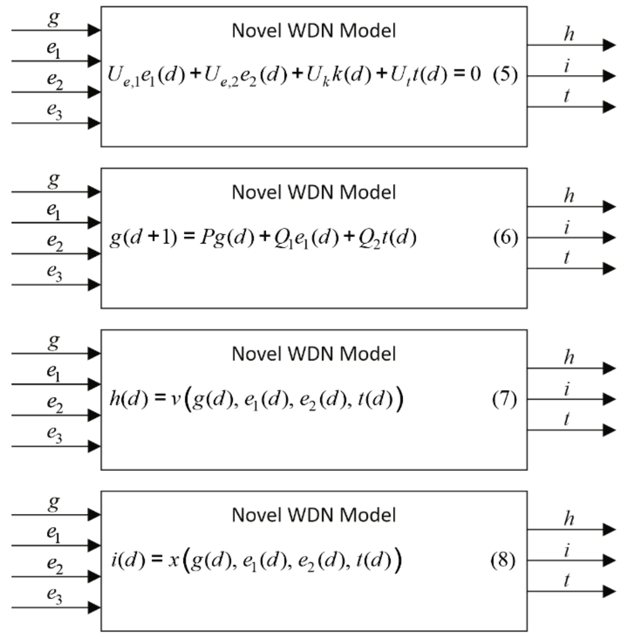

Figure 3 Novel WDN model

Overall, the WDN model Fig. 3 could be expressed as,

$$\boldsymbol{g}(d+1) = P\boldsymbol{g}(d) + Q_1 e_1(d) + Q_2 \boldsymbol{t}(d) \tag{9}$$
$$h(d) = v\left(\boldsymbol{g}(d), e_1(d), e_2(d), \boldsymbol{t}(d)\right) \tag{10}$$
$$i(d) = x\left(\boldsymbol{g}(d), e_1(d), e_2(d), \boldsymbol{t}(d)\right) \tag{11}$$
$$U_{e,1}e_1(d) + U_{e,2}e_2(d) + U_k \boldsymbol{k}(d) + U_t \boldsymbol{t}(d) = 0 \tag{12}$$

An optimization model is presented in the paper to decrease water distribution system leakage using a pressure control approach whereas.

3.2 Population based BSO

BSO is a population-based evolutionary technique employed in order to tackle numerical optimization issues with true values. The proposed model's objective function is given in Eq. (13)

$$\text{Minimize } Z = J\sum_{z=1}^{ls}\sum_{m=1}^{lh}\sum_{k=1}^{ln} S_k [A_{zmk}]^{l_k} \tag{13}$$

Where, Z is to minimize the leakage a pressure management scheme could be implemented and A_{zmk} is pressure of k^{th} node at zm instance. Where as, zm instance is refered as mth hour of z^{th} session, J is a penalty coefficient equal to 10^4 is used when the limitations on indices are violated. Otherwise, it is equivalent to one, S_k kth node's fixed leakage–pressure relation coefficient, ls number of seasons considered, lh number of hours considered in the performance period of analysis, ln total number of water distribution network nodes, S the number of water distribution network storage tanks, z the index of considered seasons ranges from 1 to ls, m in the performance period of analysis, the index of hours ranges from 1 to lh, k index of nodes ranging from 1 to ln. The hydraulic simulation framework is employed to determine nodal pressure as a function of every storage tank's water table, water demand, and node height. Higher as well as lower water elevation limitations in every holding tank,at every nodal pressures, daily and session wise pumping capacity and resilience, but also failure indices constrain the procedure. k^{th} node pressure A_{zmk} is specified by Eq. (14).

$$A_{zmk} = f(U_k, b^*_{zmk}, UR_{1zm}, UR_{2zm}, \dots\dots, UR_{Dzm})\ \forall z, \forall m, \forall k \quad (14)$$

Where z is the index of considered seasons ranges from 1 to l s. m is In the performance period of analysis, the index of hours ranges from 1 to lh. k is index of nodes ranging from 1 to ln. U_k is elevation of the k^{th} node (m), b^*_{zmk} is water demand of the k^{th} node at the m^{th} hour of the z^{th} season (l/s), UR_{zm} is at the m^{th} hour of the season, the head of j^{th} tank (m). Commulative water level of all D water tanks is modeled in Eq. (15).

$$\sum_{j=1}^{D} C_{jzm+1} = \sum_{j=1}^{D} C_{jzm} + \sum_{l=1}^{L} CA_{lzm} - B_{zm}\ \forall z, \forall m \quad (15)$$

Where C_{jzm+1}water volume in the subsequent j^{th} tank at mth hour of z^{th} season (m^3), C_{jzm} is level of water in j^{th} tank at m^{th} hour of z^{th} season (m^3), D is Number of storage tank in the water distribution network, l is index of pumps, j is index of storage tank, B_{zm} is total water demand (m^3/h) at the m^{th} hour of the z^{th} season, L is number of pumps in the water distribution network, CA_{lzm} is water discharged by l^{th} pump at m^{th} hour of z^{th} season (m^3), z is the index of considered seasons ranges from 1 to ls. m is In the performance period of analysis. Eq. (15) gives timely continuity equation for saved volume of water in the water tank during every instance. Eqs. (16) and (18) explain the network's resilience and failure indices, which are used to provide a good smallest degree of WDN for all type of variation in water level. Resilience is described as the ability to handle including an incident or a breakdown in equipment. Due to the severity of rapid head loss, it's necessary to have more energy in every node than what is needed. As a consequence, once the system has failed, this extra power is used to compensate for greater head losses. The network's capacity for dealing with an emergency improves as its resilience index improves. In water supply structure, technical fault refers to a deviation from the system's lowest needed pressure. In this case, due to a lack of pressure, the complete required requirements were met, and the system is unable to sustain a minimum goal level. WDN Resiliance indices at zm instance is calculated as follows.

$$Ir_{zm} = \frac{\sum_{k=1}^{ln} b^*_{zmk}(A_{zmk} - A_{min})}{\sum_{j=1}^{D} BR_{jzm}UR_{jzm} + \sum_{l=1}^{L}(POW_{lzm}/\gamma) - b^*_{zmk}A_{min}}\ \forall z, \forall m \quad (16)$$

Where Ir_{zm} is index of resiliency of the water distribution network at the m^{th} hour of the z^{th} season, b^*_{zmk} , is water demand of the k^{th} node at the mth hour of the z^{th} season (l/s) A_{zmk} is k^{th} node pressure at the m^{th} hour of the z^{th} season (m), A_{min} is every node must have a minimal amount of pressure (m), BR_{jzm} is discharge from the j^{th} tank at the m^{th} hour of the z^{th} season (l/s), UR_{jzm} head of j^{th} tank at m^{th} hour of z^{th} season (m), POW_{lzm} is power input to the network by pump 1 at the m^{th} hour of the z^{th} season (W), γ is specific weight of water, z is the index of considered seasons ranges from 1 to ls. m is In the performance period of analysis, to estimate the failure index for the overall infrastructure, first use Eq. (17) to estimate the failure intensity at every node, then employ Eq. (18) to calculate the failure index for the entire structure. WDN hydraulic failure index If_{zmk} at zm instance for k^{th} node is given as Eq. (17).

$$If_{zmk} = \begin{cases} 0\ \forall k: A_{zmk} \geq A_{\min} \text{ and} \\ b^*_{zmk}(A_{\min} - A_{zmk})\ \forall k: A_{zmk} < A_{\min} \text{ and} \end{cases} \forall z, \forall m, \forall k \quad (17)$$

Where If_{zmk} is k^{th} node failure index during the m^{th} hour of z^{th} season, A_{zmk} pressure of the k^{th} node at the m^{th} hour of the z^{th} season (m), A_{min} is every node must have a minimal amount of pressure (m), b^*_{zmk} is water demand of the k^{th} node at the m^{th} hour of the z^{th} season (l/s)), z is the index of considered seasons ranges from 1 to ls. m is In the performance period of analysis k is index of nodes ranging from 1 to ln

$$If_{zm} = \frac{\sum_{k=1}^{ln} If_{zmk}}{\sum_{k=1}^{ln} b^*_{zmk}A_{min}} \forall z, \forall m \quad (18)$$

Where If_{zm} is hydraulic failure index of the system at the m^{th} hour of the z^{th} season, k is index of nodes ranging from 1 to ln, ln is total number of water distribution network nodes, If_{zmk} is k^{th} node failure index during the m^{th} hour of z^{th} season, A_{min} is every node must have a minimal amount of pressure (m), b^*_{zmk} is water demand of the k^{th} node at the m^{th} hour of the z^{th} season (l/s)), z is the index of considered seasons ranges from 1 to ls. m is in the performance period of analysis.

$$A_{\min} < A_{zmk} < A_{\max} < A_{j\max}\ \forall z, \forall m, \forall k \quad (19)$$

Where A_{zmk} pressure of the k^{th} node at the m^{th} hour of the z^{th} season (m), $A_{\min}$ is Every node must have a minimal amount of pressure (m), $A_{\max}$ maximum suggested pressure at each node (m), $A_{j\max}$ is maximum permissible pressure at each node (m), z is the index of considered seasons ranges from 1 to ls. m is In the performance period of analysis k is index of nodes ranging from 1 to ln. The following various condition are applicable for optimization and given in Eq. (20) to the Eq. (24).

$$UR_{j\min} < UR_{jzm} < UR_{j\max}\ \forall z, \forall m, \forall j \quad (20)$$
$$CA_{lzm} < CA_{l\max}\ \forall z, \forall m, \forall l \quad (21)$$
$$\sum_{l=1}^{L}\sum_{m=1}^{lh} CA_{lzm} < CA_{day}\ \forall z \quad (22)$$
$$Ir_{zm} > Ir_{\min}\ \forall z, \forall m \quad (23)$$
$$If_{zm} < If_{\max}\ \forall z, \forall m \quad (24)$$

Where, the remaining variables are $UR_{j\,\min}$ minimum tank water level j (m), $UR_{j\,\max}$ is maximum tank water level j (m), UR_{jzm} head of j^{th} tank at m^{th} hour of z^{th} season (m) , $CA_{l\,max}$ maximum hourly capacity of the pump l. (m^3), CA_{day} is maximum amount of daily pumping volume required (m^3), $Ir_{\min}$ minimal resilience index for water distribution networks, $If_{\max}$ is maximum allowable failure index for a water distribution network, z is the index of considered seasons ranges from 1 to ls , m is in the performance period of analysis k is index of nodes ranging from 1 to ln, l is index of pumps,L is number of pumps in the water distribution network, lh number of hours considered in the performance period of analysis

3.2.1 Pressure Management using BSO

BSO maintains a population of I and T are water consuming vectors for this purpose. Three major genetic algorithms are used to establish BSO experimental populations (selection, mutation, and crossover). It has a random mutations mechanism which uses a 1-direction distinct for every target individual, as well as a memory that keeps a population from a arbitrarily selected earlier generations to use when setting the search-direction matrix. BSO employs five evolutionary techniques like: initialization, 1$^{\text{st}}$ selection, mutation, crossover, and 2$^{\text{nd}}$ selection. Fig. 4 depicts the overall flowchart of BSO.

Objective Function Evaluation: BSO starts by randomising nodes inside their numerical range with a uniform random distribution function:Generalized pressure at a tank is given by Eq. (25)

$$A_{z,m} \sim U(low_m, up_m), z = 1,2, \dots \dots \dots I, m = 1,2, \dots \dots T \quad (25)$$

where I indicates the seasons and T represents the storage tank in the WDN. The uniform distribution of water level is denoted by U. $A_{z,m}$ denotes the z^{th} tank individual's pressure of the mth node. low_m, and up_m are the pressure at lower and upper boundaries, accordingly.

The dependent variable constraints are combined into objective function under consideration via quadratic penalty terms as shown in Eq. (26). As a consequence, infeasible solutions that break the limitations are unlikely to be handed onto future generations. As a consequence, the objective function f can be generalised and written in Eq. (26).

$$f = F + \lambda_f \sum_{Llim_f} \Delta f_{\text{load}}^2 + \lambda_B \sum_{L\,lim_b} \Delta b_x^2 + \lambda_{ac} \Delta a_c^2 + \lambda_{cv} \sum_{Llim_{cv}} \Delta c_v^2 \quad (26)$$

Where, F is a control factor of mutation operator; λ_f, λ_B, λ_{ac}, and λ_{cv} are the penalty factors , $Llim_f$ is the water level which has exceeded their limitations. $Llim_B$ denotes the storage tank whose water levels are beyond the limits, $Llim_{cv}$ denotes the set of overflow lines, and Δf_{load}, Δb_x, Δa_c, and Δc_v are denotes water flow, reactive water flow, active water flow, and apparent water flow which is defined in following Eq. (27) to Eq. (30).

$$\Delta f_{\text{load}} = \begin{cases} f_{\text{load}}^{\min} - f_{\text{load}} & \text{if } f_{\text{load}} < f_{\text{load}}^{\min} \\ f_{\text{load}}^{\max} - f_{\text{load}} & \text{if } f_{\text{load}} > f_{\text{load}}^{\max} \end{cases} \quad (27)$$

$$\Delta b_x = \begin{cases} b_x^{\min} - b_x \text{ if } b_x < b_x^{\min} \\ b_x^{\max} - b_x \text{ if } b_x > b_x^{\max} \end{cases} \quad (28)$$

$$\Delta a_c = \begin{cases} a_c^{\min} - a_c \text{ if } a_c < a_c^{\min} \\ a_c^{\max} - a_c \text{ if } a_c > a_c^{\max} \end{cases} \quad (29)$$

$$\Delta c_v = c_v^{\max} - c_v \text{ if } c_v > c_v^{\max} \quad (30)$$

In which the superscripts 'min' and 'max' represent the variable's minimal and highest numbers.

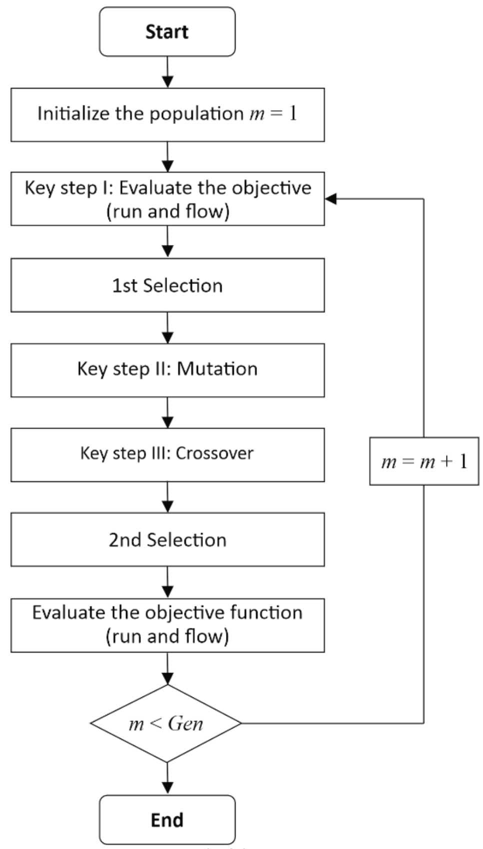

Figure 4 Flowchart of BSO in pressure management

1st Selection: At this step, BSO produces the historic demographic utilisation to determine the search direction, as shown in the formula given in Eq. (31).

$$A_{z,m}^{old} \sim U(low_m, up_m) \quad (31)$$

Where $z = 1, 2, \dots, I$, $m = 1, 2, \dots, T$, $A_{z,m}^{old}$ focuses on the historical population BSO enables consumers to rebuild the historic demographic at the start of every cycle by adhering to a rule given bellow.

$$A_{\text{old}} = \begin{cases} A & \text{if } p < q \\ A_{\text{old}} & \text{if } p \geq q \end{cases} \quad (32)$$

Where, p and $q \sim U(0,1)$ to detect if the historical population is collected from the prior generation. The shuffling algorithm is subsequently employed to reshuffle the members in the population as regards in Eq. (33) in which in which the permuting () function is a random shuffling operator.

$$A_{\text{old}} = permutting\ (A_{\text{old}}) \tag{33}$$

Mutation: The mutation process employs the subsequent procedure to produce mutant BSO vector $\boldsymbol{V}$ at every generation and accordingly control factor F is formulated as bellow.

$$F = A + \boldsymbol{V}(A_{\text{old}} - A) \tag{34}$$

Where, V is an actual value that indicates the storing tank's level of water. By taking into consideration the values of the historical population, the BSO used previous experiences to establish the water level at the storage tank.

Algorithm 1 BSA Crossover Strategy

Input: V, *mix rate*, I and T
Output: D: Trial Population
$map_{(1:I,\ 1:T)} = 0$
If $p < q \mid p, q \sim U(0, 1)$ then
for z from 1 to I do
$map_{z,\ e(1:[mixrate.rnd.T])} = 1 \mid e = permuting\ ((1, 2, 3, \ldots, T))$
end
else
for z from 1 to I do, $map_{(z,\ randz(T))} = 1$, *end*
end
D := Mutant
for z from 1 to I do
for m from 1 to T do
if $map_{(z,\ m)} = 1$ then $D_{(z,\ m)} = A_{(z,\ m)}$
end
end

Crossover Process: Algorithm 1 depicts crossover process of BSA. This procedure is divided into two stages. The initial generates a binary integer-valued matrix called as a map directing crossover locations using a mix rate. The next permits the BSA's crossover method to be employed in order to generate the trial population's final form (Algorithm 1) by using the formula given in Eq. (35).

$$D_{z,m} = \begin{cases} A_{z,m} \text{ if } map_{z,m} = 1 \\ F_{z,m} \text{ if } map_{z,m} = 0 \end{cases} \tag{35}$$

Where $D_{z,m}$ are the trial members. In BSA's crossover process, the mix rate variable defines the amount of parameters of persons which will change in a trial population.

2nd Selection: The process is then employed in the final step to evaluate the fitness of the trial vector as well as the associated target vector and pick the parent that would live in the upcoming generations, as regards:

$$A_{z,m}^{\text{next}} = \begin{cases} D_{z,m}, if\ f(D_{z,m}) < A_{z,m} \\ \quad A_{z,m} \text{ otherwise} \end{cases} \tag{36}$$

Where, $f()$ denotes the fitness function. As a result, the population either improves or remains constant in terms of objective values. Several steps are again continued via generations, and the process ends whenever the optimum number of generations are reached or some specific stopping criteria is met.

3.2.2 The Head-Driven Simulation Method

HDSM ought to be utilized to study the network for reliable leakage estimation because leakage and pressure are inextricably linked. Moreover, the EPANET software was used to model network leakage in our research. The EPANET2.0 programme is utilized to model water network hydraulic systems. This program has various features that render it suited for hydraulic study of water distribution networks as compared to alternative methods []. The emitter could be employed in every node, is one of EPANET's effective capabilities. As demonstrated here, rate of flow of water with every emitter can be computed as a in term of pressure within a specific node is specified by Eq. (37).

$$B_k = S_k A_k^{l_k} \tag{37}$$

At node k, B_k is the rate of flow of water, A_k is the pressure, S_k is the intensity of flow, and l_k is a power term. This function is useful for simulating leaks. S_k and l_k parameters must be evaluated for this purpose. The assumption is that l_k is constant and is equal to 1.18, and S_k is determined by Eq. (38).

$$S_k = S \sum_{m=1}^{j} \frac{N_{km}}{2} \tag{38}$$

Where, N_{km} is the mth pipe at kth node, and S is a network-wide constant, as illustrated below.

$$S = \frac{Leak}{\sum_{k=1}^{ln}\left(\sum_{m=1}^{j} \frac{N_{km}}{2} \times A_k^{l_k}\right)} \tag{39}$$

Where $Leak$ denotes the amount of leaking but during weakest night flow. The pressure in the preceding equation is determined at the point of least night flow.

To calculate pipe leakage, the influence of pipe average pressure must be taken into account. This suggest changes that every half-length of a pipe possesses the identical stress as its end device, which was integrated into the leakage solution via the S calculation in Eq. (39). This technique overestimates leak during the initial half while underestimating leakage in the second half, balancing the others.

After computing the S value for the entire network, Eq. (38) can be applied to determine S_k for every node, that is utilized by the hydraulic simulation study as the emitters flow rate coefficient. For faster convergence, it is critical to have a valid initial guess when calculating the S factor. The initial estimate was calculated for this reason utilizing node pressure without accounting for leakage. The leakage is estimated after the initial event, then S is updated using Newton's method and relation between new S_{new} and old S_{old} is given by Eq. (40).

$$S_{\text{new}} = S_{\text{old}} - \frac{f(S_{\text{old}})}{f'(S_{\text{old}})} \tag{40}$$

where S_{new} and S_{old} represent the earlier also innovative forecasts of S, and f is a function of the distinction among expected and measured leakages. Newton's approach was utilized until the estimated leakage equals the observed leakage value. In this case, the leakage is estimated if many actual emitter coefficients are discovered at each nodes.

3.3 CNN Model for Pressure Management

To estimate pressure variations, a numerical solution must be combined with suggested leakage decrease optimization method, as indicated in Eq. (14). Hydraulic simulator techniques are increasingly being used to describe the complex and non - linear behavior of water distribution systems. Unfortunately, hydraulic simulation models had difficulties of projecting the dynamic consequences of various control settings in respect to the baseline circumstances with short-term demand fluctuations because the inflict to the computation complexity. Furthermore, When hydraulic simulation approach are described by an I/O connection, that could be mapped to use a multivariate functional in this scenario, there is bound to be a large chance for boosting computational performance. The proposed method employs the outcomes of a water supply modeling research to develop a CNN framework. The CNN architecture's output as a water pressure function is again linked with a BSO-based optimization technique to put on water pressure and leakage at every node of the distribution system for water depends on holding tank water level, water usage, and node height.

Because the input-output connection in the CNN framework is straightforward to estimate, it may be viewed as a basic approximation of input-output computations in every descriptive or optimization technique. The advantages involve decreased runtime and simple implementation, while the drawback is a loss of precision. The trade-off must be where and how the concept is used, in addition to who the end users are. The hydraulic simulation method's outputs are employed in this study in a CNN framework which may be linked to the optimisation problem. CNN algorithms have been taught to reproduce simulated findings over time. The processing order of the optimization method could be decreased by substituting the EPANET2.0 hydraulic simulation system with CNN. It is important to underline that diminishing precision. The processing challenges could be considerably decreased as a result.

The CNN algorithm has been trained utilizing EPANET 2.2 findings for various storage tank water levels and water demands within their variation limits. The strategy can be chosen after test different multilayer feed-forward CNNs.

4 RESULT AND DISCUSSION

This section addresses the overall performance of our proposed scheme. Moreover, previous work comparison findings are compaired.

Tool: EPANET 2.2 AND PYTHON
OS: Windows 7 (64 bit)
Processor: Intel Premium
RAM: 8 GB RAM

Table 2 Network table - nodes at 1:00 hrs

Node ID	Elevation (m)	Base demand (MLD)	Pressure (m)
Junc j1	15	0.005	17.54
Junc j2	15	0.005	17.54
Junc j3	15	0.005	17.54
Junc j4	15	0.005	17.54
Junc j5	15	0.005	17.54
Junc j6	15	0.005	16.83
Junc j8	15	0.005	16.83
Junc j9	15	0.005	17.54
Junc j10	15	0.005	17.55
Junc j11	15	0.005	17.55
Junc j12	15	0.005	17.55
Junc j13	15	0.005	17.55
Junc j14	15	0.005	17.55
Junc j15	15	0.005	17.56
Junc j16	15	0.005	17.56
Junc j17	15	0.005	17.56
Junc j18	15	0.005	17.56
Junc j19	15	0.005	17.56
Junc j20	15	0.005	17.56
Junc j21	15	0.005	17.56
Junc j22	15	0.005	17.58
Junc j23	15	0.005	17.60
Junc j24	15	0.005	17.61
Junc j25	15	0.005	17.57
Junc j26	15	0.005	17.56
Junc j27	15	0.005	17.55
Junc j28	15	0.005	17.54
Junc j29	15	0.005	17.58
Junc j30	15	0.005	17.58
Junc j31	15	0.005	17.64
Junc j32	15	0.005	17.64
Junc j33	15	0.005	17.70
Junc j34	15	0.005	17.70
Junc j35	15	0.005	17.70
Junc j36	15.5	0.005	17.22
Junc j37	15.5	0.005	17.22
Junc j38	15.5	0.005	17.21
Junc j39	15.5	0.007	17.33
Junc j40	15.5	0.007	17.65
Junc j41	15.5	0.007	17.65
Junc j42	15.5	0.007	17.67
Junc j43	15.5	0.007	17.87
Junc j44	15.5	0.007	18.31
Junc j45	15	0.007	18.81
Junc j46	15.5	0.007	18.31
Junc j47	15.5	0.007	18.31
Junc j48	15.5	0.007	18.31
Junc j49	15.5	0.007	18.31
Junc j50	15.5	0.007	18.31
Junc j51	15.5	0.007	18.31
Junc j52	15.5	0.007	18.31
Junc j53	15.5	0.007	18.31
Junc j54	15.5	0.007	18.31
Junc j55	8	0.013	24.71
Junc j56	8	0.013	24.71
Junc j57	8	0.013	24.71
Junc j58	8	0.013	24.71
Junc j59	8	0.013	24.70

4.1 Dataset Description

The details of water supply network from City and Industrial development Corporation of Maharastra limited

(CIDCO)is collected. This CIDCO contains details of drawings of Water Supply Network and Elevated Storage Reservoir (ESR) / High Storage Reservoir (HSR) and Master Balance Reservoir (MBR) of Kharghar Node. This water distribution system in Kharaghar requires effective water management for both supply and demand.Overall, the system's fundamental issues identified is leakage.

It is proposed that Pressure management is the easiest, shortest, but possibly least cheap approach for reducing leakage in kharghar water distribution systems. The drop in network pressure leads to a reduction in leakage rate. Added pressure beyond the absolute lowest value promotes systems resiliency, while pressure deficiency (underneath the lowest permissible value) contributes to request shortfall, in which customers cannot be fully provided. As a result, the optimum combination of numerous decision variables could be found to use a search strategy including BSA to calculate the appropriate level of pressure. As per the CIDCO rule, 650 litres of water have to be supplied per flat per day.

The overall amount of junction in the network is 840, number of reservoir is 1, number of tanks is 9, number of pipe is 831 of various diameter such as 100 mm, 150 mm, 200 mm, 250 mm, 300 mm, 350 mm, 400 mm, 450 mm, and above 500 mm. The network has a total number of PRV valve as 130 and roughness coefficient as 110. Moreover, the pressure value is taken for per hour, as a result, we have taken the 6 hour pressure value. The collected 1 hour pressure value data sample is tabulated as Tab. 2.

Then, the obtained EPANET 2.2 values are fed into the proposed Neural Network based Optimization model. The collected data's are processed through the PYTHON to find out the water pressure and leakage.The maximum pressure value as 327.68 is set, if the pressure value is exceed this limit it will be considered as a leakage. Lastly, the proposed method is contrasted with the current framework to demonstrate its effectiveness. The following is a Tab. 3 of the proposed CNN's structure.

Table 3 Architecture of the proposed CNN

Layer Type	Specifications
Convolutional layer 1	Kernel Size: 5×5; Filter: 64; Stride: 3×3; Padding: Same
Max pooling layer 1	Pool Size: 3×3; Stride: 3×3 Padding: Same
Convolutional layer 2	Kernel Size: 5×5; Filter: 128; Stride: 3×3; Padding: Same
Max pooling layer 2	Pool Size: 3×3; Stride: 3×3 Padding: Same
Convolutional layer 3	Kernel Size: 5×5; Filter: 256 Stride: 3×3; Padding: Same
Max pooling layer 3	Pool Size: 3×3; Stride: 3×3 Padding: Same
Fully Connected Layer	Size: 64
Output Layer	Size: 1

4.2 Performance of Proposed Model

This section assesses the effectiveness of the proposed system, where *Precision*, *Accuracy*, *Recall*, *F1 Score*, and loss metrics were used to assess the proposed prototype.

4.2.1 Loss vs Epochs Graph

The training loss of a proposed Neural Network Based Pressure Optimization Model, which measures the difference between the model's predictions and the actual target values in the training dataset, is used to assess the model's performance. More precise forecasts and efficient identification of underlying patterns in the training data are indicated by a smaller training loss. As the model goes through multiple epochs of iterative optimization, the training loss trend steadily decreases. In just 5 epochs, the model reached a training loss of less than 0.0682, demonstrating a rapid convergence to remarkably accurate predictions on the training set. Low training loss over a short period of epochs indicates successful data collection and learning.

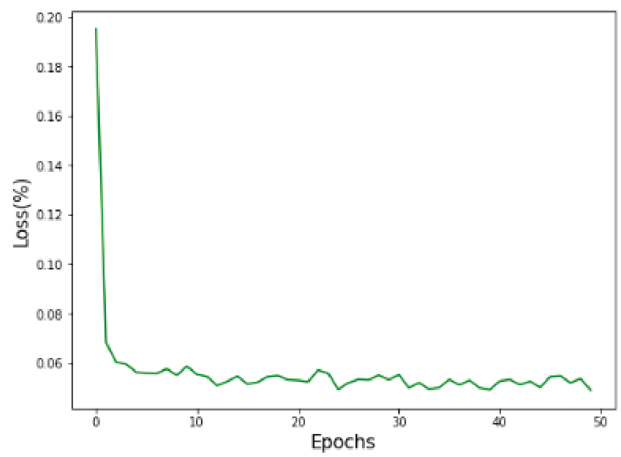

Figure 5 Loss vs Epochs Graph proposed approach

4.2.2 Performance Parameters

This chapter provides an overview of our proposed methods, in which several metrics including *Accuracy*, *F1 Score*, *Precision*, and *Recall* were used to evaluate the unique method's effectiveness in water distribution system pressure optimization. Various performance indicators, includes *Accuracy*, *Precision*, *Recall*, and *F1 Score*, were evaluated using the Eqs. (41)-(44).

$$Accuracy = \frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + False\ Positive + False\ Negative} \quad (41)$$

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \quad (42)$$

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \quad (43)$$

$$F1\ Score = \frac{2*Precision*Recall}{Precision + Recall} \quad (44)$$

The novel approach of the model—which combines a Convolutional Neural Network (CNN) with the Backtracking Search Optimization algorithm—allows it to precisely identify positive cases and classify instances within the dataset with low misclassification rates. The suggested approach's excellent levels of *Accuracy*, *Precision*, *Recall*, and *F1 Score* attest to its applicability and promise for real-world uses in a variety of fields where precise classification is critical. Overall, the results show that the suggested method is dependable and effective at handling classification jobs with a high degree of precision and accuracy.

4.3 Comparison Results

This chapter discussed the proposed method's comparative study, In this study, which the our technology is comaired with the methods like Nave Bayes, Logistic Regression, and Convolution Neural Network (CNN).

4.3.1 Accuracy Comparison

In terms of accuracy, the suggested method performs better than baseline models such as Naive Bayes, Logistic Regression, and conventional Convolutional Neural Network (CNN). With an accuracy rate of 99.80 %, the approach outperforms Logistic Regression by 98.23 %, Naive Bayes by 95.49 %, and standard CNN by 98.62 %. This improvement in performance highlights the usefulness and edge of the new strategy over traditional techniques. The results presented in Tab. 4 validate the effectiveness of the suggested methodology and show that it is more accurate than baseline models and sophisticated techniques. It also shows that it has the potential to outperform current methods in real-world applications.

Table 4 Overall Accuracy

Methods	Accuracy (%)
Naïve Bayes	95.49
Logistic Regression	98.23
Convolution Neural Network (CNN)	98.62
Proposed Method	99.80

4.3.2 Precision

A comparison of the precision levels between the suggested strategy and alternative techniques is presented in Tab. 5. The suggested strategy performs 98 % better than the BSO-based CNN method and 98.23 % better than the Naive Bayes model, demonstrating its efficacy and superiority over conventional techniques. The strategy significantly improves the accuracy and reliability of the classification task, achieving an excellent precision rate of 99.80 %. These results confirm the effectiveness of the new approach and highlight its potential to beat current approaches in real-world scenarios where great precision in classification tasks is required. The suggested method is a major improvement over traditional procedures.

Table 5 Overall Precision

Methods	Precision (%)
Naïve Bayes	98
Logistic Regression	98.23
Proposed Method	99.80

4.3.3 Recall Comparison

The recall performance of the suggested method is contrasted with other approaches in Tab. 6. The usefulness and superiority of the suggested strategy over conventional approaches are demonstrated by its 95.40 % and 99 % performance gains over the BSA-based CNN method and Logistic Regression method, respectively. The technique produces an astounding 100 % recall rate, which is a major improvement over earlier solutions and a notable improvement in the dataset's ability to detect pertinent cases. These results confirm the new strategy's effectiveness and highlight its potential to beat current approaches in real-world scenarios where good recall in classification tasks is needed.

Table 6 Overall Recall

Methods	Recall (%)
Naïve Bayes	95.40
Logistic Regression	99
Proposed Method	100

4.3.4 F1-Score Comparison

A comparison of the *F1 Scores* of the suggested strategy with other approaches is presented in Tab. 7. The suggested method shows its superiority in terms of *F1 Score*, outperforming both Logistic Regression and the BSA-based CNN method by 99.10 % and 97.65 %, respectively. With a remarkable *F1 Score* of 99.90 %, the approach significantly enhances the model's capacity to strike a balance between recall and precision. These results demonstrate the usefulness of the unique strategy and its superiority over conventional ways in producing better outcomes.

Table 7 Overall F1 Score

Methods	F1 Score (%)
Naïve Bayes	97.65
Logistic Regression	99.10
Proposed Method	99.90

5 CONCLUSION

The appropriate hour water level fluctuations in a water distribution storage tank with various seasons are explored in proposed research. To estimate the effective mechanism, the pressure that exists at various network nodes under various operating circumstances are evaluated. To acquire better precise pressure measurements at various nodes of network, the quantity of leakage quantity at each node is analysed. Because it requires awhile to integrate the hydraulic simulation and optimization algorithms, a CNN algorithm is trained to predict the system's hydraulic properties. Directly linking a hydraulic simulation with the BSO, design leads to enhance the accuracy of the output. While the optimization method is designed for a large collection of storage containers. The study's findings can be applied to other components of the structure. In this example, the optimal water volumes in over-all accessible storage facilities are utilised with CNN output in addition to BSO model decision factors. Whenever a software like this technique are utilised in a realistic situation, the network's associated to water supply could be planned better effectively by minimizing 31.5 % leakage. The findings show that there is a need of implementing a combined solution toolkit to ensure the efficient functioning of the water distribution system.

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