Eng Int Syst (2024) 5: 521–532
© 2024 CRL Publishing Ltd

Engineering
Intelligent Systems

Investigation and Design of Drainage Network Renovation Engineering in Residential Areas Based on BP Neural Network

Bai Fang[1,a*] **and Ranmao Hu**[2,b]

PowerChina Huadong Engineering Corporation Limited, Hangzhou 311122, Zhejiang, China
Wenruitang River Engineering Construction Center of Ouhai District in Wenzhou, Wenzhou 325000, Zhejiang, China

Nowadays, residential district drainage systems play a significant role in designing and investigating renovation projects to prevent water contamination and stormwater runoff. After investigating the challenges associated with existing urban drainage pipeline systems, including runoff and its impact on society and the environment, an efficient drainage network renovation is proposed, which is essential for residents' health and quality of life. A deep learning (DL) technique called backpropagation neural network for residential drainage renovation (BPN2-RDR) is employed in district drainage network projects. Firstly, existing residential drainage infrastructures and the associated challenges are investigated. Secondly, optimized design parameters, including pipe flow, channel capacity, and slopes for controlling runoff, are adopted for the renovation strategies. The training of the neural network model with pertinent data obtained from Waipa district council, including 766 records and 36 attributes, enables the discovery of various design patterns and the identification of the relationships of the parameters within the drainage network system. The design phase utilizes the trained neural network to predict potential issues and optimize the drainage system for enhanced performance. For performance evaluation, the proposed method is analyzed using metrics such as peak flow reduction rate of the drainage system, accuracy, precision, recall, and Root Mean Square Error (RMSE). The result findings confirm the superiority of the proposed algorithm when applied to the district residential drainage network renovation projects, thereby enhancing the residents' quality of life.

Keywords: Backpropagation, deep learning, neural network, design parameters, residential drainage network, renovation project, stormwater.

1. BACKGROUND INTRODUCTION

The residential work in the Waipa district drainage network renovation project includes upgrading the infrastructure through drainage pipes, inspection chambers, and utility hole sewer fixtures improved with modern design parameters to carry the residential wastewater to accommodate larger runoff volumes and reduce the risk of flooding. In general, residents in this district produce two distinct wastewater types. The first one is household utensils wastewater that does not produce harmful bacteria, and the second one is from washrooms that produce harmful bacteria called sewage wastewater. Both types of wastewater are managed by the drainage network and discharged into a common catchment, the municipal drain, located outside residential boundaries. The general diagrammatic representation of a drainage network project in a residential district is depicted in Fig. 1.

Drainage networks serve as crucial stormwater systems that carry surface runoff to appropriate bodies of water to ensure the health and safety of residents by mitigating major drainage overflows [1] and flooding of streets. According to the state of the drainage structure, the renovation may involve various tasks like leakage repairs, material replacement for

*Corresponding Author
[a]Email: 15088772194@163.com
[b]Email: 76140587@qq.com

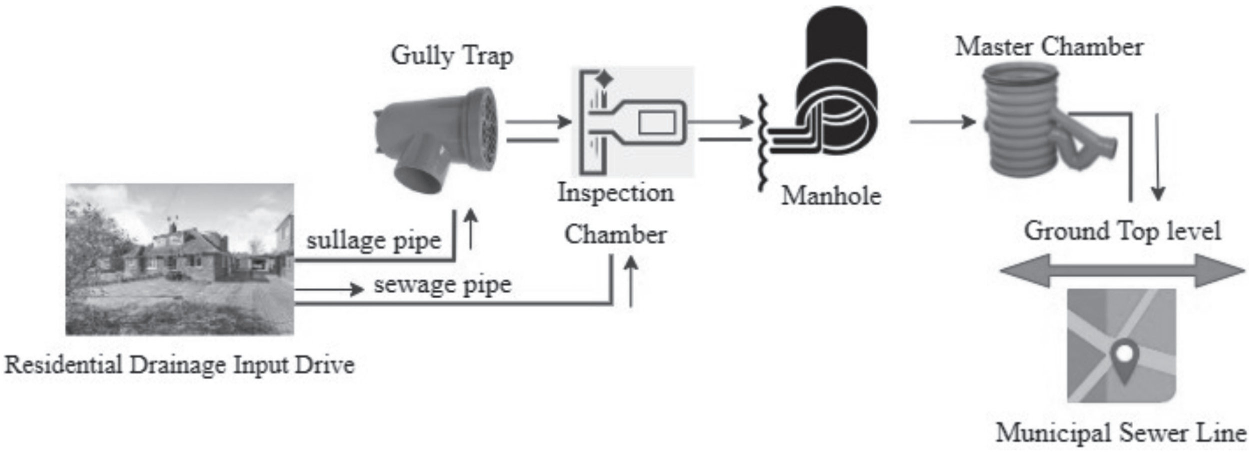

Figure 1 General arrangement of residential drainage system.

defective or ruined parts, insulation deployment, or sewer line improvements [2]. Because of its strong and complex data-training capabilities, the neural network [3] is well suited to handling complicated system modelling and control issues. Being a complicated system that changes with non-linearity and ambiguity, a city's drainage network makes it difficult to develop an analytical computational framework model [4]. The main issue is a lack of knowledge of storm drainage construction [5], necessitating the design of fixes and taking precautions to guarantee overflow diversions in inadequate subsurface drainage networks. The effectiveness of improving the sewage system's quality and efficiency was assessed. The condition of the water at the point of intake and outflow location, together with the amount of gathered sewage, has significantly improved since the drainage system renovation project [6] began. An important and difficult task involves investigating various design aspects of drainage networks, especially the damaged pipe [7] structures such as inlet, flow, outlet, slow drainage, and corresponding maintenance strategies.

The building materials used in drainage renovations and the usefulness of applying Artificial Neural Networks (ANNs) to comprehend and anticipate complicated interactions have been explored [8]. A competent pipe network system is also built thanks to quality and security monitoring [9] during the building process. To provide adequate services for residents, the water distribution and drainage network design should conform to people-oriented thinking and ensure that the drainage channels are not obstructed. Numerous issues confront drainage management systems including combined sewer overflows, bacteria and other disease-bearing organisms in surface waters, floods, and the resulting residential property damage [10]. The existing drainage network maintenance for residential districts includes generalizing the pipeline network, catchment basin locations, runoff measures of stormwater, and monitoring pathways and flow rates [11]. Prescreening is needed to monitor chemicals and pollutants in a drainage network system with proper sensor sites [12]. Whenever the choice of the water transportation locations is unclear, the pipe determination's layout design and diameter are optimal simultaneously by considering the topographical and hydraulic restrictions [13]. In [14], the dense residential region of various locations was analyzed using clustering approaches with the renovation strategies of catchments and optimal location of roofs.

The advantage of renovation ideas in residential areas is that improving the quality of drainage water supply and enhancing the aesthetic benefits of waterways are inevitable even though the economic aspects have not been properly assessed [15]. The renovation proceeds sequentially, considering the optimal time and cost investments related to renovation projects and making appropriate decisions to prevent flooding during natural disasters [16]. Designing and researching a home's drainage network are interrelated and help drainage rehabilitation efforts succeed [17].

Research contributions

1. Investigate the feasibility of flooding and runoff challenges in existing drainage network systems and propose a novel renovation approach.
2. Design new drainage model parameters with appropriate infrastructure related to pipelines, flow capacity, and soil types.
3. Recruitment of local authorities as decision-makers and investigating of the renovation strategies' roles in maintaining the drainage network project using a trained neural network.

The remainder of this research article is organized as follows: (2) previous studies are examined; (3) the renovation project of drainage network using a neural network trained using the proposed algorithm is presented in detail; (4) the algorithm is evaluated and discussed using a data source and compared with benchmark schemes; and (5) conclusions, potential limitations and recommendations for further research are discussed.

2. PREVIOUS STUDIES

Chen et al. (2023) optimized a model based on Neural Networks (NN) using statistical analysis, genetic algorithms

(GA), and data from bioretention ponds that were still in operation [18]. The model successfully predicted pollutant removal efficiency, which also identified positive and negative correlations between variables such as the amount of soil erosion and the rainfall period. The results for accuracy and representativeness were 69% and 93% respectively, with an average removal ratio of ammonia and nitrite nitrogen. Weather-related surface factors impact biological retention reservoir performance.

Hameed (2022) developed and evaluated the ANN models using a backpropagation algorithm for maintaining irrigation and drainage projects [19]. The researcher determined the validity and verification of the designed NN model using independent variables such as length, cost, area, and thickness associated with a dependent variable: the total duration of the contract. The result was a Mean Percentage Error (MPE) of 0.952, an accuracy of 89.37%, and a Root Mean Square Error (RMSE) of 1.359. However, the factors underlying these results were not explained.

Fei (2023) studied the modelling and optimal water level forecasting drainage network control using the Long Short-Term Memory (LSTM) model with Grey Correlation Analysis (GCA) [20]. Investigating drainage pumping stations with high correlation factors produced better accuracy, less RMSE, and inflexion point tracking ability. The data for result analysis was taken from the XM sewage pumping station pipeline from a city from 2021 to 2022 with the 1 min sampling period analysis. The efficacy of the grey correlation strategy is contingent upon specific presumptions, and its suitability may differ depending on the attributes of the data.

Chandale & Patil (2022) used the Digital Elevation Model (DEM) to identify ridge lines in the Basin Delineation (BD) [21]. Using Landsat images and ArcMap support, they performed supervised classification to determine the area of the impervious region, finding that 43% of the area contained buildings and roads. Using MIKE, the urban 660+ connections were digitalized for a region, exported, and imported.

Bakhshipour et al. (2021) proposed a multiobjective decision-making platform for the modern sustainable design of urban drainage systems with centralized and decentralized infrastructures [22]. The performance indicators were resilience in terms of both structural and operational layouts, sustainability, and stakeholders' approval. The generated results were optimized using pareto front results in a non-dominated manner. Numerous hybrid design schemes were produced, combining aspects of grey, blue, and green colours with varying sewage designs and levels of (de)centralization. However, this research only allowed for a limited set of sewage designs to be simulated.

Febrianto et al. (2023) implemented a Lamongan Residential Drainage System that was built using models developed by the Hydraulic Engineering Centre-River Analysis System (HEC-RAS) and the Storm Water Management Model (SWMM) [23]. This is shown by the fact that there are instances of severe flooding during the rainy season. The flooding height in the residential complex is within 60 cm, decreasing by more than 12 hours. According to the computed findings, several parts of the canal experienced runoff, with an anticipated Q5 flood flow of 8.14 m3/sec. Surveys in the field revealed that the renovations to homeowners' residences had altered the widths of several waterways. This research used SWMM and HEC-RAS software to conduct 1D channel hydraulic modelling. The goal was to create a model that closely matched the surface runoff conditions at the study location.

Despite the advantages and improvements that current strategies demonstrate in renovating the drainage network in the residential districts, limitations discussed still need to be focused on, such as topographical restrictions, the impact of surface features, inadequate stormwater drainage design, controlled drainage infrastructures, and limited curve number of pipeline flow capacity [25]. Hence, the proposed algorithm targets the renovation of residential drainages which is a significant factor; this is in contrast to the existing benchmark schemes such as GA-NN [18], LSTM-GCA [20], and HM-SWMS [23] which are analyzed for performance evaluation and comparison.

3. PROPOSED METHODOLOGY

Typically, drainage renovation entails making upgrades or modifications to drainage infrastructure to increase the renovation project's effectiveness. The renovation aims to tackle problems with the state of the water, flooding, soil deterioration, and faulty drainage networks. An overall diagrammatic representation of the proposed BPN2-RDR is shown in Fig. 2.

Data Source Description

The data was obtained from a publicly available dataset [24] with a link describing the drainage channels involved in the stormwater network resources. The researchers gathered previously unsurveyed information and historical assets of existing drainage network infrastructure centred with various dimension boundaries, types of drains, pipes, and their condition. Fig. 3 shows a map of the residential side storm water drainage systems of a district.

The assurance from the Waters Asset management team at Waipa District Council with the data table consisting of 766 records and 36 attributes. The attribute focused on the swales region comprises linear landforms that have gently sloping sides and serve as drainage channels. The detailed drainage network parameters are given in Table 1.

Designing a Neural Network Architecture

With the DL framework, TensorFlow implements the neural network describing objectives, including renovating the residential drainage system, predicting the stormwater runoff, and evaluating the effectiveness of different renovation strategies. Input features like soil type, slope of land within the residential boundary, and existing drainage infrastructure in residential areas are included in the input layer of the neural network,

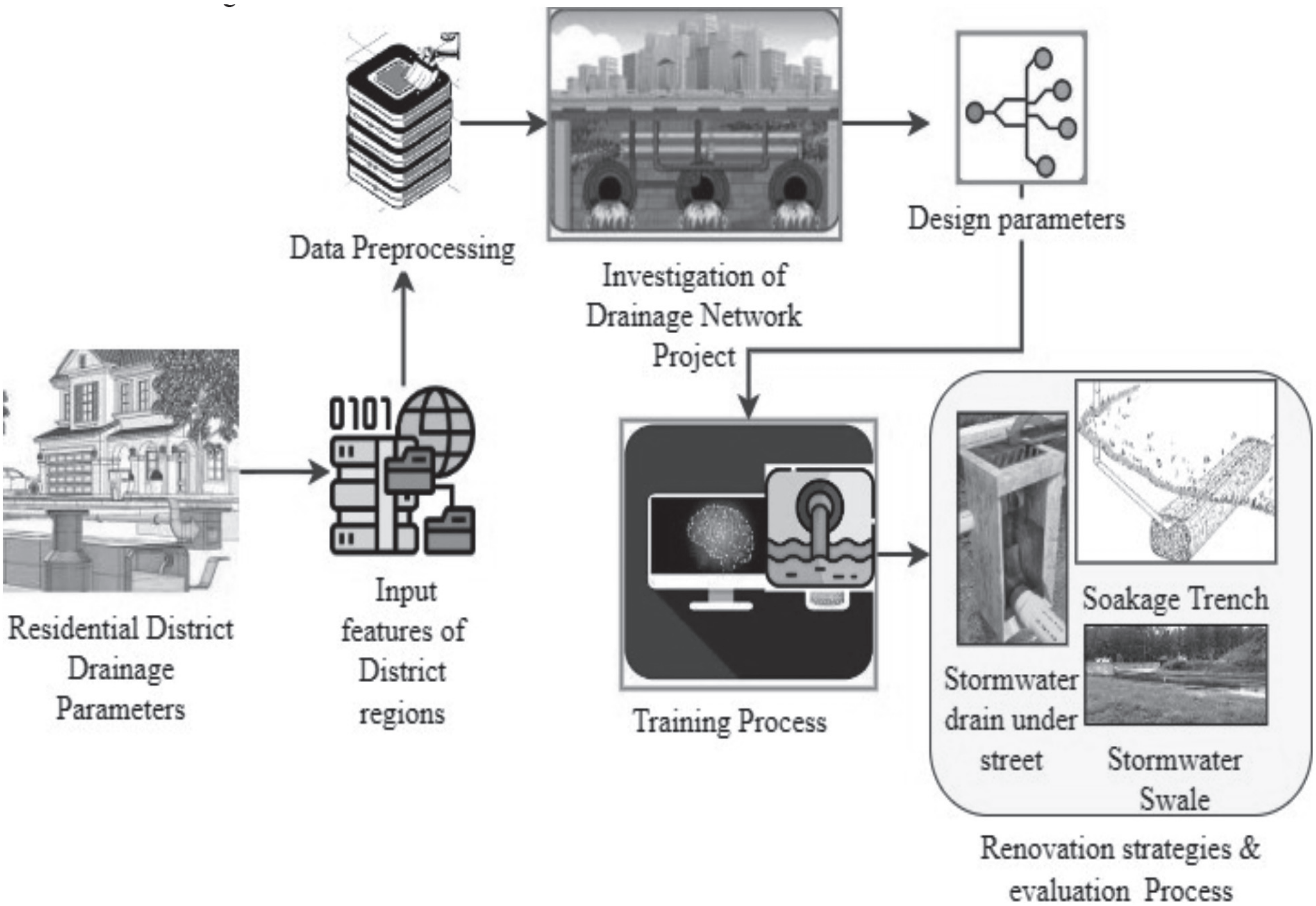

Figure 2 The schematic representation of the proposed BPN2-RDR Model.

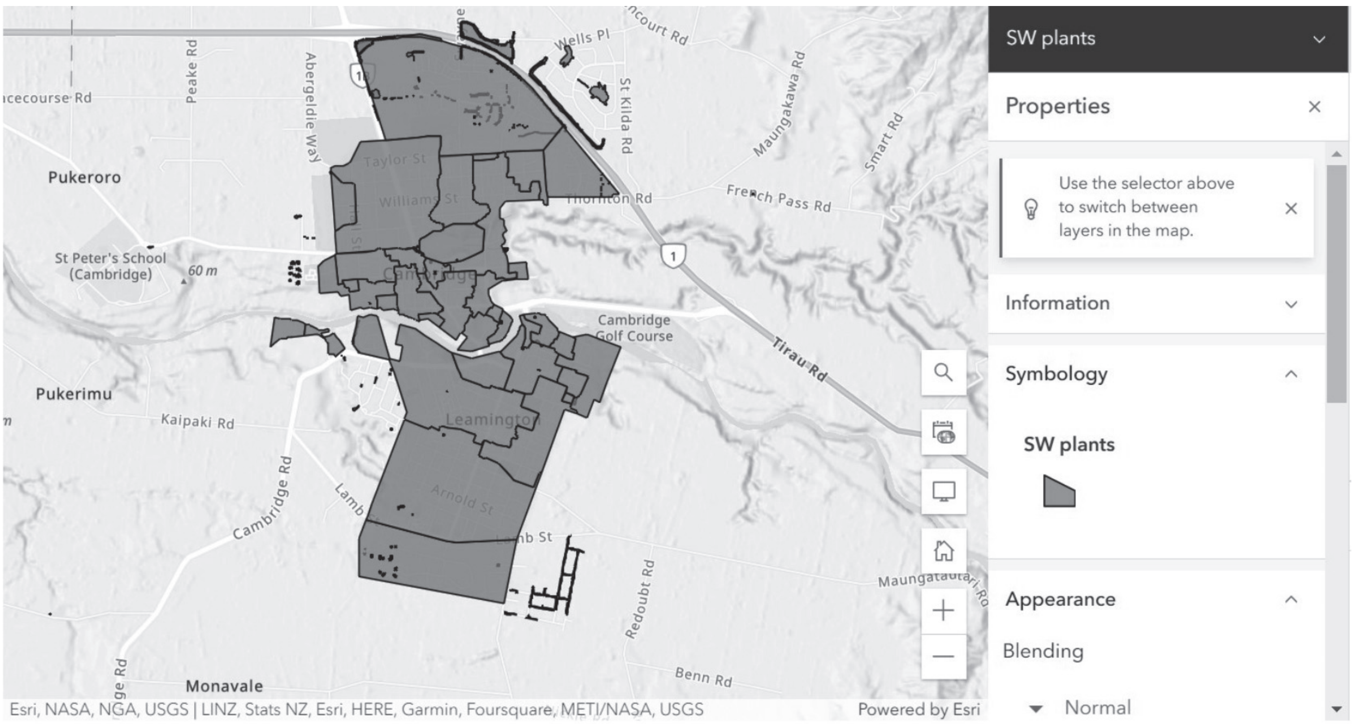

Figure 3 Map of stormwater district drainage system.

Table 1 Drainage Network Parameters.

Drainage Asset Types	Parameter Ranges
Stormwater Trench	Distribution pipe-150mm dia, three perforated liners with HD lid.
Soakage trench	Soil, rock formed swale, pipe, catch pit, retention pond
Material	Rock, natural ground, concrete, Galvanised Steel
Drainage Condition /Performance	Excellent, good
Accuracy	Good, very poor, excellent, average
Criticality	Medium, very high,
Location	Footpath, road centre, verge, grass-berm, scruffy-dome
Shape Area (m2)	553986.9375
Shape Length (m)	6269.76925749705

and the optimal output will be the coordinates or locations for the optimal drainage renovation project, recommended drainage system modifications, and predicted stormwater runoff. Throughout the residential drainage network project, decisions could be made based on the neural network's projected outcomes. The Rectified Linear Unit (RELU) activation function, the appropriate loss function RMSE, and the Stochastic Gradient Descent (SGD) optimisation algorithm are chosen. The neural network-based technique seeks to reduce the possibility of floods, maximize stormwater management, and help anticipate the best sites for residential drainage renovations.

Data Preprocessing

Data preprocessing involved data cleaning and handling missing values using mean imputation because it simply ignores the correlation among input features such as soil types, pipe capacity, and slope variants of asset types. These missing values are filled with the mean of all the available data and the statistical information is preserved. The inputs that pose outliers have to be removed, which can impact the training process of renovation strategies using a neural network model. The residential drainage features show categorical types of information; hence, the one-hot encoding process is applied for categorical variables that can easily be input into a machine learning model.

Investigation of the Residential Drainage Network Project

Because of the impact of uneven house fence construction, which blocks off a portion of the drainage pathways and makes it harder for rainwater to enter, homes vary in size. The inspection chamber is placed along the sewer pipe outlet, similar to the manhole at the drainage network's corner blocks. Both sewage pipelines and sullage flow because of gravity force from the drainage pipe outlet in residential areas. A gully trap (GT) is a small-sized chamber that provides access to any blockage in the drainage pipeline, and its purpose is to act as a connection chamber for the drainage sullage pipeline between residential apartments. The GT water seal prevents foul gas from flowing through the sullage. All the residential vertical drainage pipelines pass their sullage waste to the GT above ground level.

The flow of wastewater through the draining pipeline is maintained at the slope of the normal gradient at the range of 3%. The drainage pipeline with a maximum diameter of 9 inches is used to interconnect the manholes and inspection chamber. The maintenance holes are usually constructed with brick, cement, or UnPlasticized Polyvinyl Chloride (UPVC) reinforced fibre. The municipal sewer line usually runs below ground, whereas the plumbing fixtures in the residences, such as the floor trap, are placed at the highest level. The municipal sewer line is connected with the residential drainage network maintenance hole through the master inspection chamber. The management of these chambers, along with the sewer pipeline at a minimum of 6 feet below the ground level, is taken care of by local authorities known as 'municipal bodies' to prevent reverse flow across the residential boundaries.

It is necessary to renovate the infrastructure dimensions, that is, the layout of the drainage ditch system, to prevent flooding caused by the channel's overflowing water levels. Based on the current channel, it has been determined that the dimensions of the previously used distribution cannot accommodate and drain the designed flood discharge. Before renovating the drainage network system, the designer must investigate the supply network in terms of the materials used, appropriate design layout parameters, and defined standards of pipeline parameters usage. The best sustainable management practices must be maintained to reduce the impact of stormwater runoff on the quality and quantity of water. Detention basins and tanks must be constructed on various streets such as Vogel Street, Preston Road, and Victoria Street shown on the map. They should include green infrastructure components such as stormwater-based bioswales and driveway gardens in residences.

Designing Parameters of Drainage Network Project

The parameters are: maximum diameter max_α of a pipe in terms of meter(m), maximum depth max_β of all pipes in the drainage network in terms of meter(m), maximum flow velocity $max_{\rho,t}$ at m/s where ρ denotes the flow of velocity over a time t, and water quality standards. When renovating, the existing drainage infrastructure must be evaluated and optimized to meet current and future demands, considering pipe capacity, slope, and flow paths. The infrastructure is comprised of 20mm Galvanised tendons deployed to a max_β

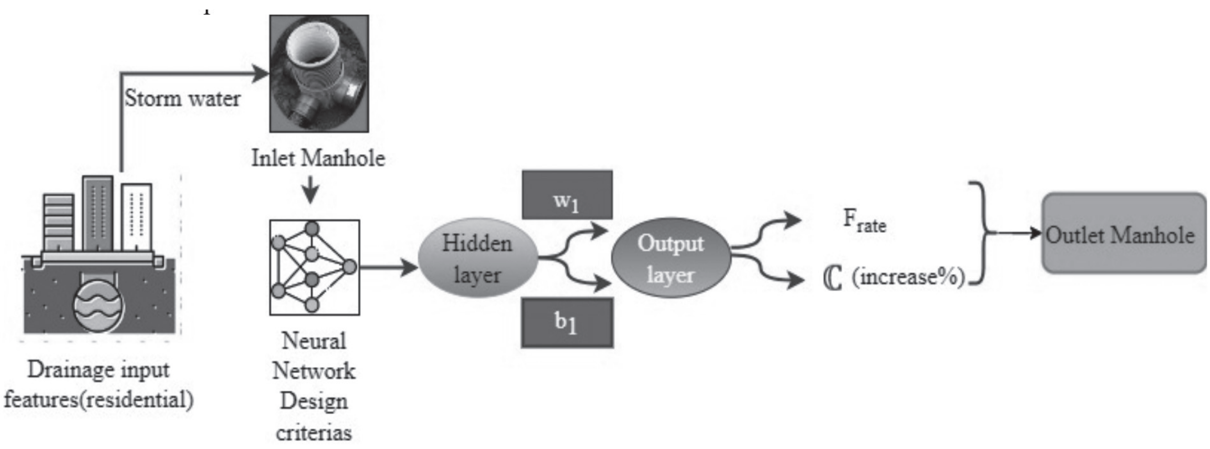

Figure 4 Schematic representation of design parameters.

9.0m and fitted with 300 × 300 × 100mm galvanised plate and hex nut to ensure MacMatt R to slope range. The suggested pipe materials are cast iron or PVC pipe. The objective is to increase the capacity $\mathbb{C}$ of the residential district street drainage pipeline network using design parameters like *post* $\mathfrak{R}_{\mathbb{C}}$ post renovation capacity and the *pre* $\mathfrak{R}_{\mathbb{C}}$ prerenovation capacity using equation (1).

$$\mathbb{C}(increase\,\%) = \frac{(post\ \mathfrak{R}_{\mathbb{C}} - pre\ \mathfrak{R}_{\mathbb{C}}\ )}{pre\ \mathfrak{R}_{\mathbb{C}}} \times 100\% \quad (1)$$

In addition, the $\mathbb{C}$ of a drainage pipeline can be estimated using Manning's formula of roughness coefficient denoted as n. The cross-sectional flow area of square feet is defined as A followed by hydraulic radius R in feet. S is defined as the slope of the channel bed.

$$F_{rate} = \frac{1}{n} \cdot A \cdot H(R)^{2/3} \cdot S^{1/2} \quad (2)$$

Fig. 4 illustrates the two extreme conditions in the boundary line corresponding to each pipe length using equation (2), and its connectivity between maintenance holes with the inflow of stormwater runoff entrance over a time instant in terms of hours is valuable.

Training Process Implementation Details of Neural Network

The backpropagation technique is applied to learn the renovation requirements of drainage. A neural network is also used with the training input dataset to predict the optimal location of drainage renovation. This requires continually adjusting the biases and weights for minimal loss function to reduce the discrepancy between the expected and actual results. It was found that the neural network trained on 100 epochs with a batch size of 32 gradients can be applied successfully to new designs for drainage, which can be assessed using the testing dataset. The init_network() is a function used to create a new neural network that can be used to train the dataset for the renovation of the drainage network. The function mentioned above accepts three arguments: the number of inputs and the count of neurons that are not. of_hidden neurons with the no. of_inputs+1 weights to be in the hidden layer with xy coordinates for locating the renovated drainage network with new ideas and additional bias followed by the corresponding renovated output layer no.of_outputs of the residential drainage network project with a weights range of no.of_hidden+1.The weight w indicates the number of neurons that will be activated with the added bias b as a constant value.

Fig. 5 illustrates that for a layer with no. of_inputs+1 weights with input functions and n_{in} connections, the corresponding weights are initialized with Gaussian distribution with mean 0 and variance $\frac{2}{n_{in}}$.The weight matrix of each layer, the element representation for each connection from input, is given as w_{xy} and from hidden to the output layer is w_{xy} are considered to be drawn from the same distribution with initialization called $w \sim G\left(0, \frac{2}{n_{in}}\right)$. Initializing the network's learning parameters for renovation involves randomly selecting weights from the above distribution. The non-linearity to the N2 is introduced by the RELU activation function in the hidden layers with a learning rate α can be set as 0.001 or 0.01.

The training procedure for the BPN2-RDR Model

init_network()
fn init_network(n_{in}, hidden_neurons, n_{out})
init w and b(n_{in}, hidden_neurons, n_{out})
return(w(no.of_hidden), b(no.of_outputs))
# BP training model for a residential drainage renovation project
fn train_BPN2 (model,training_data, epochs(100), batch_size=32, $\alpha = .0001$)
    for epoch in range(epochs):
        shuffle(training_data)
            for batch in get_batches(training_data, batch_size):
inputs,targets=extract_inputs_targets(batch)
#forward pass with design parameters
h_input=dot_pdt(n_{in}, mode1[0]) + mode1[1]
h_output= RELU (h_input)
in (n_{out})=dot_pdt (h_output, mode1[2])
predictions= RELU (in (n_{out}))
# Calculate RMSE loss function
loss=cal_RMSE (predictions, instance_targets)

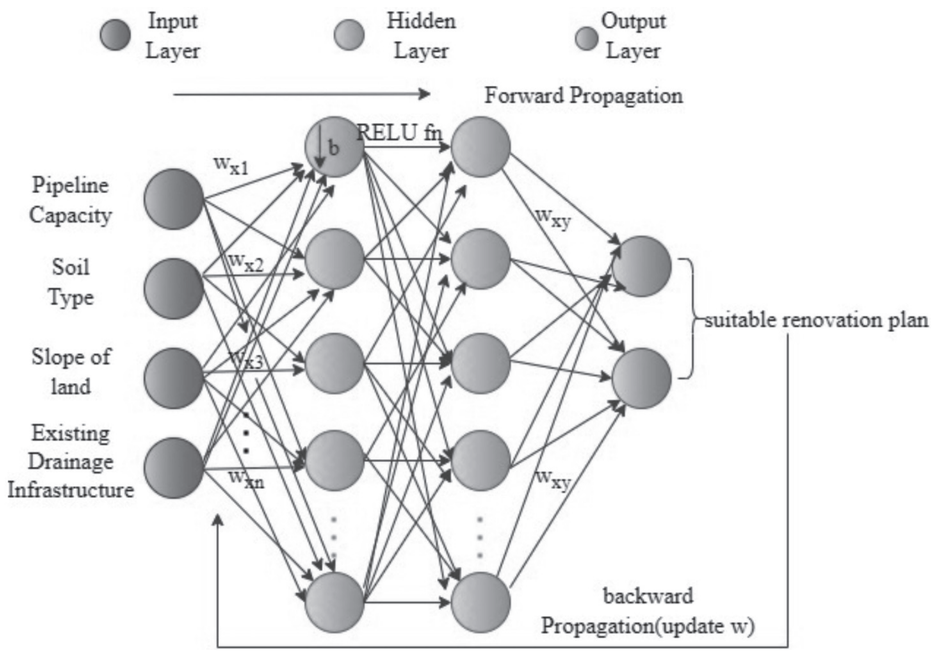

Figure 5 Back propagation neural network architecture for residential drainage renovation.

#Backward pass
evaluate output_err,hidden_err
update w and b using gradient descent patterns with $G\left(0, \frac{2}{n_{\text{in}}}\right)$
end for
return the trained BPN2 model for optimal drainage renovation

The batch size is the size of the data chunk implemented during each iteration, either in small or large portions of selected regions of land usage in terms of unit range. The learning rate refers to how quickly the proposed BPN2-RDR model adapts to its adjusted hyperparameter range based on the feedback from the training data, with a significantly greater count indicating major alterations in the applied renovation strategies in the residential districts.

Dropout is a regularization strategy in which neurons are discarded randomly throughout the training phase, either by including or excluding certain strategies in the overall renovation plan for a robust outcome of the training dataset. One hyperparameter that helps to reduce overfitting is the dropout rate, which controls the likelihood of neurons being discarded in a particular layer. The neural network's design architecture for drainage infrastructure comprises decisions regarding the number of neurons in every single layer and the total number of hidden layers. It is better to have smaller learning rates α that result in slower performance than having many training repetitions. For the next subsequent layers of the BPN2-RDR model, the output of the neuron is given with the sum of activated input neurons added with bias represented using equation (3).

$$n_{out} = \max(0, w(sum\ of\ n_{in} + b) \tag{3}$$

Instead of choosing the quickest weights of parameters to minimize variance, a process known as 'early convergence' increases the probability that the network can identify an appropriate combination of renovation possibilities with the corresponding features in every network layer. Each fully connected layer is trained with the following renovation ideas. The testing set determines its effectiveness, which shows how well the newly-trained renovation strategies work in their respective districts in the neighbourhoods of residential premises.

Integration with Drainage Renovation

The renovation of drainage networks in residential areas uses sustainable stormwater maintenance that utilizes soakage trenches to manage and control stormwater runoff. The objective is to minimize surface runoff and help prevent surface flooding. This is particularly helpful in cities and suburbs because impervious surfaces like pavements and roads accelerate drainage. A narrow, straight trench below the surface lined with gravel sits beneath a subterranean ventilated pipe known as a 'soakage trench'. Including a drainage trench in a drainage system renovation requires careful consideration of various elements such as soil type, infiltration rates, and any unique features of the residential district or urbanized area. Soakage trenches can be entirely underground and undetectable or help define borders or margins within the existing drainage environment. Firstly, a hole approximately two feet in width and depth is dug to evaluate the soil's capacity for drainage. Water is added to the hole, allowed to empty and then refilled to determine how quickly the water disappears. The location is excellent for a soakage trench if the water in the hole drains in < 1 day, around 1"/hour. In this type of renovation, the modular design material comprises polypropylene copolymer. The size of a soakage trench can be estimated using the following equation (4).

$$len\ (st) = \frac{area(roof) \times sizing\_factor}{infiltration\_rate} \tag{4}$$

where $area(roof)$ represents the area that contributes the runoff to the st valued in sq. ft and the $sizing\_factor$ is a dimensionless factor based on the soil type in the region and the drainage conditions near to the residential premise. Infiltration_rate is the rate at which water can infiltrate the soil, measured in inches/hour. In this context, the “infiltration rate” is the rate in inches per hour at which water may seep into soil. Instead of using “ratio” to express the connection between two values, it is more appropriate to use “rate” to convey the speed or velocity of the process being described (water infiltration in this instance). “Infiltration rate is the rate at which water can infiltrate the soil, measured in inches/hour.”

By solving numerous problems associated with stormwater management and improving the drainage system’s general sustainability and effectiveness, stormwater swales can be very helpful in renovating residential drainage. Swales’ natural coverage and moderate slopes designed to slow down stormwater discharge will be in the following equation (5) range.

$$swale\_size = top(t) * base(b) * depth(d) \tag{5}$$

$swale\_size$ is the size of the corresponding drainage network; the parameter, $top\,(t)$, is as the width of the top of the swale in feet(ft); $base(b)$ is the width of the base of the swale, also measured in feet(ft), and $depth(d)$ is the depth of the swale, also measured in feet(ft). As a result, there is less chance of soil erosion, safeguarding residential areas’ soil integrity and avoiding sedimentation in adjacent water bodies. The sizing of well-drained soils of a residential area is intended to maintain the integrity of the soil in nearby residences with approximately 750 sq.ft of the rooftop to be managed; the soakage trench can be a maximum of 15 feet long with a sizing factor of 0.020.

Appropriate renovations can be made to the drainage infrastructure by adding riprap, a rock armor erosion detection measure. Swales’ vegetation and moderate slopes are designed to slow down stormwater runoff. As a result, there is less chance of soil erosion, safeguarding residential areas’ soil integrity and preventing water accumulation in neighbouring watercourses. The sizing of riprap for erosion protection in district residential drainage can be estimated using equation (6):

$$Riprap(size) = 300 \times \left(\frac{F_{vel} \times Crtical\_Shear\_Stress}{acc_{gravity}}\right)^{1/3} \tag{6}$$

Where F_{vel} denotes the velocity of water flow (in feet per second); the $Crtical\_Shear\_Stress$ is the minimum $Shear\_Stress$ required to prevent erosion measured by pounds/sq.ft. The gravitational acceleration force constant is represented as $acc_{gravity}$ with the default value of 32.2ft/s^2. Based on evaluations and forecasts of drainage infrastructure, the suggested method may be used for homes with restored drainage networks that have the correct inlet and outflow and for homes along gradient slopes and channel banks that feature tiny ponds and retentions.

These could include increasing drainage pipeline capacity, streamlining flow channels, implementing sustainable management practices, and checking the effectiveness of the renovated residential district drainage network. The effectiveness of renovation strategies can be determined by inputting proposed changes and assessing predicted outcomes.

Early stopping is applied as a regularization technique that can stop training iteration values once the model performance on validation data samples starts deteriorating. The proposed system paves the way for residential drainage systems that are more adaptable and sustainable in the face of changing environmental and demographic factors. The results make a valuable contribution to urban water management and provide insights into the use of AI in infrastructure development projects. Integrate the trained neural network into the decision-making process for renovating the drainage network. The decision-making method for upgrading the drainage network easily incorporates the trained model, offering sustainability and agility in the face of shifting socioeconomic and environmental variables [26].

4. COMPARATIVE ANALYSIS

The comparative analysis used peak flow reduction rate, accuracy, precision, recall, f1-score, and RMSE. Previous research studies such as GA-NN [18], LSTM-GCA [20], and HM-SWMS [23] are followed for performance comparison with the proposed algorithm.

Peak Flow Reduction Rate

A greater peak-level F_{rate} reduction indicates better runoff management and control by the stormwater drainage system. The result can lessen the chance of overflowing during heavy rainfall or storm activity. Reduction in peak rates of flow F_{rate} helps to lessen the detrimental impact and is easy to calculate mathematically. These measures are critical to minimizing soil loss, preserving drainage path credibility, and preventing soil deposition in nearby watercourses in residential areas. Table 2 shows the experimental setup.

When it comes to peak inflow reduction rate, as shown in Fig. 6, the suggested approach performs better than the existing alternatives, such as GA-NN [18], LSTM-GCA [20], and HM-SWMS [23]. Therefore, it can be concluded that the suggested BPN2-RDR is the best means of controlling drainage challenges and minimizing the flow.

Accuracy Analysis

As shown in Fig. 7, greater accuracy indicates that the neural network’s algorithm successfully anticipates renovating the infrastructure of residential drainage network boundaries. The ratio of accurately predicted instances of renovation occurrences in the region with particular characterstics in response to the flow rate of total instances possible is used to calculate the level of accuracy. It clearly indicates a BPN2-RDR model’s performance regarding overall design conditions or associated findings. The categorical values shown in Figure 7 denote the effectiveness of a renovation project $\mathfrak{R}_{\mathbb{C}}$, indicating it as very poor, average, good, excellent. The accuracy of drainage condition indicates that the investigated residential drainage asset is in ‘very good’ or optimal condition, ‘good’ denotes the satisfactory condition of

Table 2 Experimental Setup.

Parameters	Parameter Description
Number of Nodes	10, 20, 50, 100
Hidden Neurons	11,22,55,110
Output Nodes	1,2,5,10
Total Weights	133
Total Bias	11
CPU	Intel i7/i9 or AMD Ryzen 7/9
GPU	NVIDIA RTX 3080/3090
RAM	16 GB minimum, 32 GB
Storage	SSD with at least 512 GB for fast read/write operations.
Programming Language	Python 3.8
Deep Learning Framework	TensorFlow 2.x
IDE/Code Editor	Jupyter Notebook, PyCharm, or VS Code
Libraries & Dependencies	CUDA Toolkit

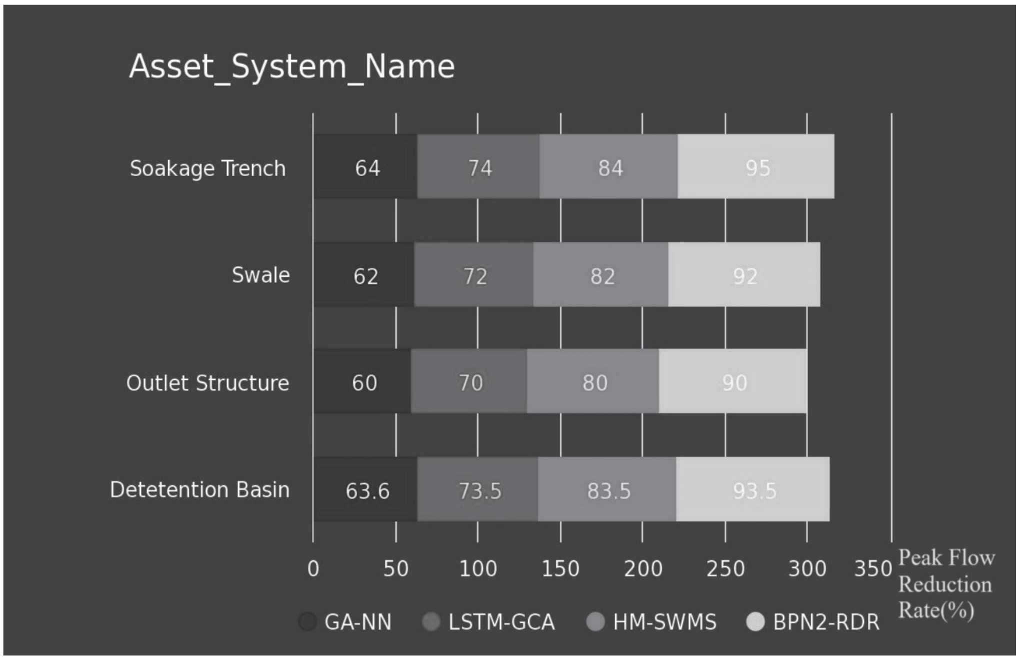

Figure 6 Peak flow reduction rate on varying system asset types.

the drainage asset. It might not be flawless, but at least it works well for renovations involving updated pipeline capacity and slope updates and functions well enough.

Precision

The selection of the forecasting cutoff impacts precision analysis and can change the ratio of false positives to false negatives by altering the threshold amount. Recall and precision are helpful when handling specific issues with drainage networks. Recall evaluates the BPN2-RDR model's capacity to capture every positive instance, whereas precision determines the correctness of implementing the accurate estimates using equations (7) and (8).

$$precision = \frac{tp}{tp + fp} \tag{7}$$

$$recall = \frac{tp}{tp + fn} \tag{8}$$

A degree of greater precision (Fig. 8) and recall (Fig. 9) means that the model is probably accurate when it predicts something positive will take place, such as the effective renovation of a drainage network project. The term 'true positives' or tp represents the number of assets after they underwent the renovation strategy correctly classified as being in an 'excellent' state. The other measure, called false positives fp, indicates the number of asset types incorrectly classified as 'good' or 'excellent'. The measuring value fn indicates the number of assets in 'good' condition after the renovation.

RMSE Analysis

RMSE is a technique used to select models according to error prediction outcomes. The current error shows the degree to which the estimated outcome deviates from the

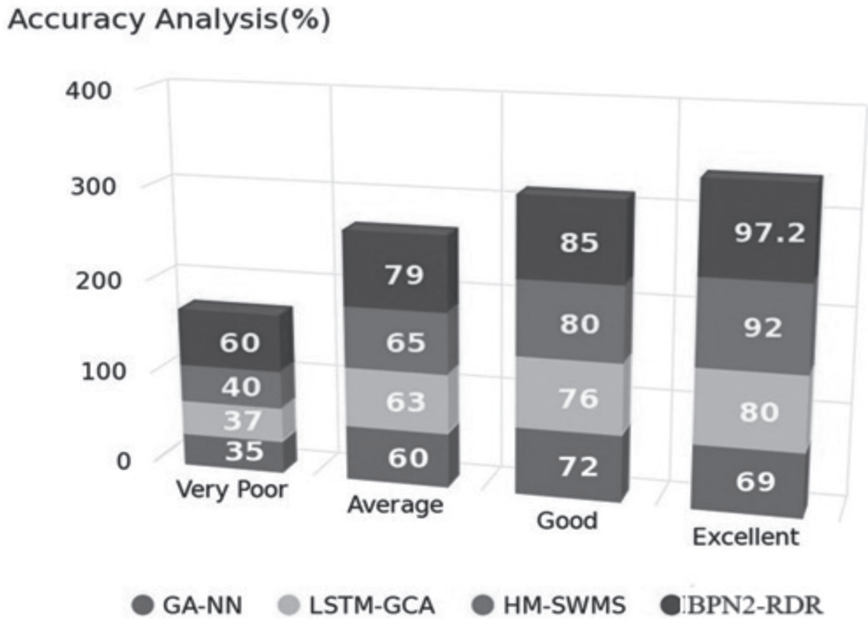

Figure 7 Accuracy analysis of drainage infrastructures.

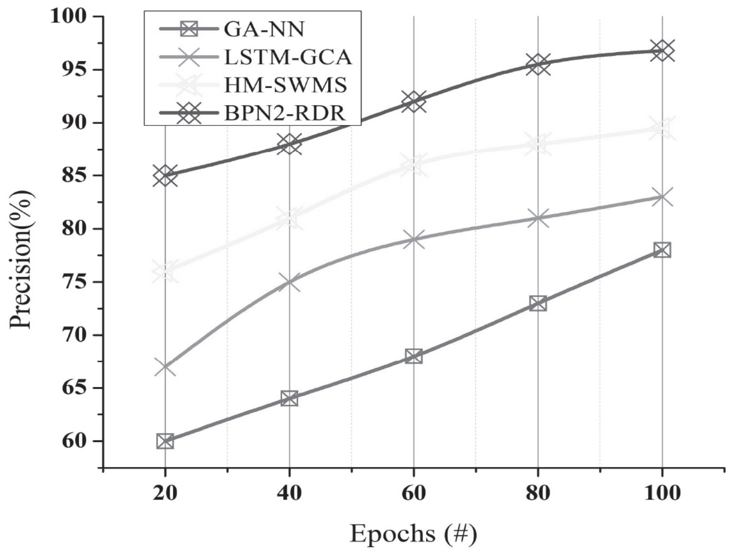

Figure 8 Precision analysis of renovated drainage infrastructures.

value that has to be estimated. If the suggested model's average is the smallest, each road segment's root-mean-square (RMSE) results should be derived from the planned drainage network source. As given in [24], the overall number of instances is 700+ data about the residential district drainage network related to the system points of information or instances in the data set, as depicted in Fig. 10.

5. CONCLUSION

The proposed BPN2-RDR can contribute to applying renovation ideas and optimising design patterns for drainage pipeline flows other than those in residential areas. The implemented renovation strategies such as soaking trenches, infiltration rates, storm swales, and soil type analysis help control stormwater runoff and maintain the good condition of drainage infrastructure compared to earlier strategies. The study examines the obstacles produced by various materials for drainage transmission lines, sewage lines, and observation facilities in residential areas. The research highlights the necessity of renovating drainage structures to mitigate flooding and manage anticipated flood occurrences by reducing peak flow rates through optimal pipelines. Sustainable stormwater management techniques, such as soakage trenches and drainage swales, have been incorporated with drainage renovation techniques. The sizes of these structures are carefully determined by considering the drainage conditions, soil type, and soaking rates. Dropout is also considered a regularization mechanism during the backpropagation learning of the recommended neural network using the BP model. Early stopping is used to prevent overfitting, and testing datasets are used to assess the model's performance.

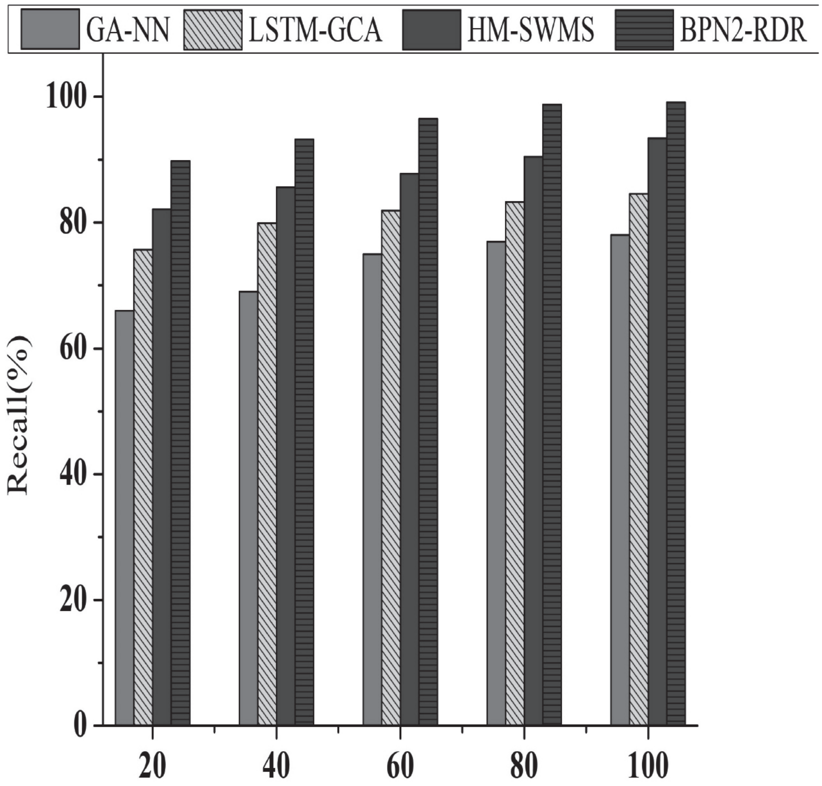

Figure 9 Recall analysis of the drainage renovation project.

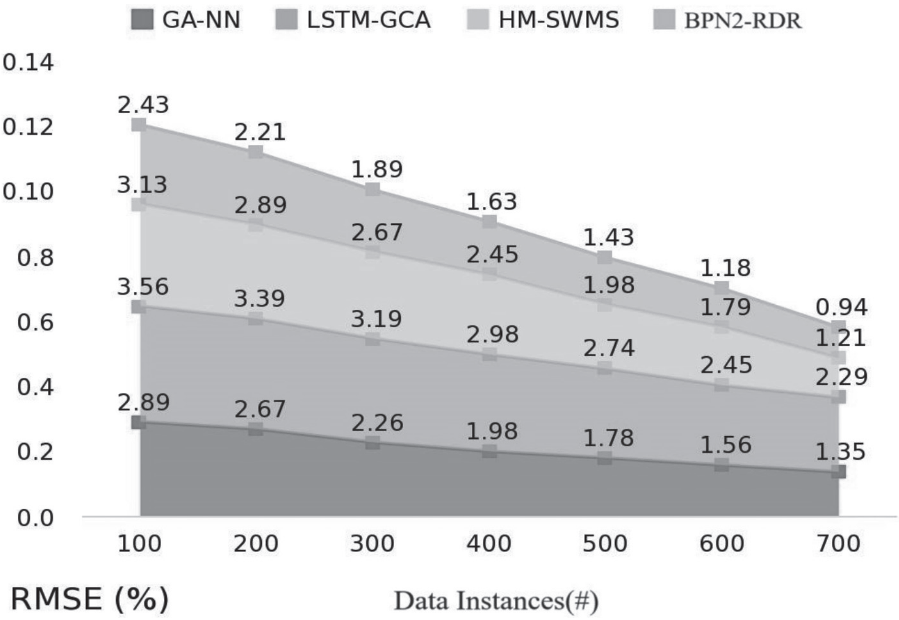

Figure 10 RMSE analysis of varying drainage data instances.

LIMITATION

Implementing drainage renovation projects based on neural networks may face compatibility issues when integrating existing drainage infrastructures with advanced training algorithms. The proposed algorithm might not be applicable during sudden environmental changes and natural disasters.

FUTURE ENHANCEMENT

The challenges mentioned above will be addressed in the future by training the learning algorithm with the implementation cost of the drainage network pipeline to improve economic and weather aspects, including frequent rainfall patterns**.**

REFERENCES

1. Li, J., Strong, C., Wang, J., & Burian, S. (2023). An event-based resilience index to assess the impacts of land imperviousness and climate changes on flooding risks in urban drainage systems. Water, 15(14), 2663.
2. Rogulj, K., Jajac, N., & Batiniæ, K. (2023). Flat Roofs Renovation Planning on Public Buildings Using Fuzzy Multi-Criteria Analysis. Sustainability, 15(7), 6280.
3. Jin, N., Yang, F., Mo, Y., Zeng, Y., Zhou, X., Yan, K., & Ma, X. (2022). Highly accurate energy consumption forecasting model based on parallel LSTM neural networks. Advanced Engineering Informatics, 51, 101442.
4. Fang, Z., Wang, Y., Peng, L., & Hong, H. (2021). Predicting flood susceptibility using LSTM neural networks. Journal of Hydrology, 594, 125734.
5. Kostina, A. A., Vladimirova, A. A., Basamykina, A. N., & Kameristaya, M. A. (2022, April). Stormwater management in cities: the way to protect geocomponents from the pollution. In IOP Conference Series: Earth and Environmental Science (Vol. 1010, No. 1, p. 012054). IOP Publishing.
6. Lin, X., Li, S., Fang, H., Fu, S., Zhou, W., Wang, J., ... & Ying, F. (2023). Performance evaluation of a typical sewage system remediation project in Yangtze River protection. In E3S Web of Conferences (Vol. 369, p. 01004). EDP Sciences.
7. Gurmu, A., & Mudiyanselage, P. W. (2023). Plumbing defects in residential buildings: analysis of anomalies and their causes. Facilities, 41(13/14), 927–956.
8. Ujong, J. A., Mbadike, E. M., & Alaneme, G. U. (2022). Prediction of cost and duration of building construction using artificial neural network. Asian Journal of Civil Engineering, 23(7), 1117–1139.
9. El-kenawy, E. S. M., Ibrahim, A., Bailek, N., Bouchouicha, K., Hassan, M. A., Jamei, M., & Al-Ansari, N. (2022). Sunshine duration measurements and predictions in Saharan Algeria region: An improved ensemble learning approach. Theoretical and Applied Climatology, 1–17.
10. Aravind, K., Krishnan, M., Devassy, M., Tharakan Renjith, N., & Rajalakshmi, T. R. (2022). Design of Storm Water Management System for the Water Stressed Areas in Palakkad District. In Climate Change and Water Security: Select Proceedings of VCDRR 2021 (pp. 447–459). Springer Singapore.
11. Zhang, Z. (2022). Simulation Study on the Effect of Sponge Transformation in Old Neighborhoods Based on XP Drainage Model Construction. In Journal of Physics: Conference Series (Vol. 2152, No. 1, p. 012030). IOP Publishing.
12. Sambito, M., & Freni, G. (2021). Strategies for improving optimal positioning of quality sensors in urban drainage systems for non-conservative contaminants. Water, 13(7), 934.
13. Duan, X., He, W., Wang, Y., Liu, Q., Tian, Y., & Shi, X. (2022). Optimization design method of a large-scale multilevel gravity drip irrigation pipe network system based on atom search optimization. Journal of Irrigation and Drainage Engineering, 148(7), 04022023.
14. Movahedinia, M., Hashemy Shahdany, S. M., & Barakhasi, F. (2022). Integrated approach for low impact development locating in dense residential areas based on sustainable development criteria. Water Science & Technology, 86(6), 1590–1612.
15. Polyakov, M., Iftekhar, M. S., Fogarty, J., & Buurman, J. (2022). Renewal of waterways in a dense city creates value for residents. Ecological Economics, 199, 107468.
16. Wang, T., Liu, B., Liu, S., Zhang, K., & Ma, M. (2023). A Two-Stage Investment Decision-Making Model for Urban Rail Transit Drainage Renovation. Systems, 11(6), 280.
17. Bai, F., Hai-zhong, Y., & Ran-mao, H. (2023). Troubleshooting Design of the Drainage Pipe Treatment Project of the Higher Education Expo Park in Ouhai District, Wenzhou City.
18. Chen, F., Zhang, Q., Chen, S., & Yuan, Y. (2023). Research on operation efficiency prediction and optimization of biological retention system based on GA-BP neural network model. Sustainability, 15(14), 10990.
19. Hameed, A. A. (2022). Development of Duration Estimation Model for Irrigation and Drainage Projects Using Neural Network. NeuroQuantology, 20(6), 3041–3053.
20. Fei, X. (2023). Urban Drainage Network Scheduling Strategy Based on Dynamic Regulation: Optimization Model and Theoretical Research. Intelligent Automation & Soft Computing, 37(2).
21. Chandale, K., & Patil, K. A. (2022). Basin Delineation and Land Use Classification for a Storm Water Drainage Network Model Using GIS. In Recent Trends in Construction Technology and Management: Select Proceedings of ACTM 2021 (pp. 561–570). Singapore: Springer Nature Singapore.
22. Bakhshipour, A. E., Dittmer, U., Haghighi, A., & Nowak, W. (2021). Toward sustainable urban drainage infrastructure planning: a combined multiobjective optimization and multicriteria decision-making platform. Journal of Water Resources Planning and Management, 147(8), 04021049.
23. Febrianto, R., Bisri, M., & Cahya, E. N. (2023). Analysis of Made Lamongan Residential Drainage System Using SWMM (Storm Water Management Model) and HEC-RAS (Hydraulic Engineering Centre-River Analysis System) Models.
24. https://catalogue.data.govt.nz/dataset/stormwater-network-stormwater-structures
25. Pan H. (2024). Application of 5G Wireless Communication and BIM Technology in Management of Construction Projects. International Journal of Engineering Intelligent Systems, 32(3).
26. Sun W. S., Lin H. (2024). Convolutional Neural Network-Based Robot Path Planning and Equipment Obstacle Intelligent Recognition System. Journal of Engineering Intelligent Systems, 32(3).