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A development of a bridge management system using the LIRF-DBiLSTM approach with the DSF-MPO algorithm

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Research Article

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A development of a bridge management system using the LIRF-DBiLSTM approach with the DSF-MPO algorithm

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Abstract: Bridge infrastructure has greater economic, social, and cultural value. The majority of the infrastructural assets are in poor condition. Therefore, a timely and accurate inspection as well as a planning strategy is required. Prevailing works failed to cover different types of bridges with diverse maintenance costs. To solve these issues, a Linear Interpolated Ridge Function based Deep Bidirectional Long Short Term Memory-centric Bridge Management System (LIRF-DBiLSTM-centric BMS) is proposed in this research method. Primarily, the bridge inventory system data is obtained. Afterward, by utilizing the Delta Scored Density-Based Spatial Clustering of Applications with Noise (DS-DBSCAN) approach, the bridge types are clustered. The damage history and repair history of the particular bridge are extracted from the clustered bridge type. Then, from the clustered bridge types as well as damage and repair history, the attributes are extracted. Thereafter, for predicting the damaged part with location, the extracted attributes and the land seismic data are provided as input to the classifier. The prioritization process is performed by using the Bridge Condition Index (BCI) and Normalized Pi-Functional Membership Function-based Fuzzy Inference System (NPFMF-FIS) if damage occurs. Next, for the prioritized damage, the management factors are derived. After that, concerning minimum cost and user delay rate, the factors are optimized utilizing Dynamic Stepsize Function-based Marine Predator Optimization (DSF-MPO). According to experimental analysis, a minimum cost with a minimum delay rate is obtained by the proposed framework. Moreover, the proposed approach attains 98.86% in damage prediction.

Keywords: *Bridge Management System (BMS), Dynamic Stepsize Function based Marine Predator Optimization (DSF-MPO), Linear Interpolated Ridge Function based Deep Bidirectional Long Short Term Memory (LIRF-DBiLSTM), Delta Scored Density-Based Spatial Clustering of Applications with Noise (DS-DBSCAN), Normalized Pi-Functional Membership Function based Fuzzy Inference System (NPFMF-FIS), Bridge Condition Index (BCI), and Damaged and repair history.*

1. INTRODUCTION

Civil structures and infrastructures have played a major role in the economy and have facilitated the daily life of the world population over the past years (Flah et al., 2021). These infrastructures have performance degradation owing to aging, environmental erosion, natural or man-made hazards, and so on (Wei et al., 2020) (Wu et al., 2021). Thus, a more effective Bridge Management System (BMS) is required. It involves inspection, planning, monitoring, and maintenance processes (Okazaki et al., 2020). As per the National Bridge Inspection Standards (NBIS), the highway bridges within the National Bridge Inventory (NBI) shall be routinely inspected every two years; in addition, the condition ratings of bridge components are recorded in the NBI database (Liu & Zhang, 2020). Hence, the manual Bridge Inspection (BI) was time-consuming. Therefore, automated infrastructure construction, inspection, and planning have been employed recently by utilizing Artificial Intelligence (AI) approaches (Dorafshan & Azari, 2020) (Miao, 2021). Furthermore, for the detection of cracks and other

damages, numerous techniques are utilized. However, the bridges have various structures and shapes as well as several special-shaped components with complex mechanical properties. It makes the automated BMS complex (Favarelli & Giorgetti, 2021) (Zhou, 2022). Therefore, for the BMS, an advanced Machine Learning (ML) model is needed (Avci et al., 2021). In this research method, a LIRF-DBiLSTM-centric BMS is proposed.

1.1 Problem statement

The limitations of the prevailing work are provided as,

- Prevailing research works failed to develop a bridge maintenance system for diverse types of bridges as per their maintenance cost.
- Owing to land seismic activity, misclassification might be presented.
- During the maintenance process of the existing (Jaafaru & Agbelie, 2022), the delay rate was increased.
- The unbalanced maintenance process of the bridge might be provided by prevailing (Corbally & Malekjafarian, 2024).
- Owing to without considering all parts of the bridge, an error output might be produced by prevailing (Fang et al., 2023).

1.2 Objectives

The objectives are,

- To group the similar bridge types by utilizing DS-DBSCAN.
- For considering the land seismic data.
- To include the cost reduction as the objective function.
- For including the damage and repair history of the bridge.
- To consider the total bridge inventory system.

The paper is structured as: the prevailing works are described in Section 2, the proposed LIRF-DBiLSTM-centric BMS is explained in Section 3, the performance analysis is described in Section 4, and Section 5 concludes the paper with future improvement.

2. RELATED WORK

(Jiang et al., 2023) presented a framework that was integrated with the ML model. To assess bridge corrosion, the ontological knowledge base was also utilized by the approach. According to experimental analysis, the developed method had superior accuracy. However, for diverse bridge structures, the framework was complicated.

(Civera et al., 2022) propounded an automated method with an ML approach for Structural Health Monitoring (SHM). As per the experimental analysis, for the masonry structures and their damage evaluation, the approach was more reliable. Nevertheless, the framework was highly reliable only for arch bridges; therefore, for other bridges, the approach was unreliable.

(Karaaslan et al., 2021) presented a decision support system and considered the aspects of the BMS. The main aim of the study was to achieve adaptive and flexible decision-making for bridge decision strategy. The experimental outcome displayed that superior performance was attained by the framework. Owing to the hybridized approach, the complexity issue was presented.

(Akintunde et al., 2021) concentrated on enhancing damage detection with the aid of an unsupervised ML approach. For varying levels of damage, the index value was generated by the framework. When contrasted with the traditional method, the result of the research was superior. But, for larger data, the Singular Value Decomposition (SVD) approach was computationally expensive.

(Althaqafi & Chou, 2022) established an Artificial Neural Network (ANN) for enhancing the BMS by considering the deterioration of bridge decks, superstructures, and substructures. The larger bridge condition evaluation was executed. According to experimental analysis, superior accuracy was obtained by the method. Nevertheless, the performance of the system might be affected by the factors of the ANN.

3. PROPOSED LIRF-DBiLSTM BASED BMS

In this research, for the damage prediction of the bridge, the Linear Interpolated Ridge Function based Deep Bidirectional Long Short Term Memory (LIRF-DBiLSTM) is utilized. The approach has three functions, such as sensor-centric inspection, monitoring, as well as planning and maintenance. Figure 1 depicts the block diagram for the proposed methodology.

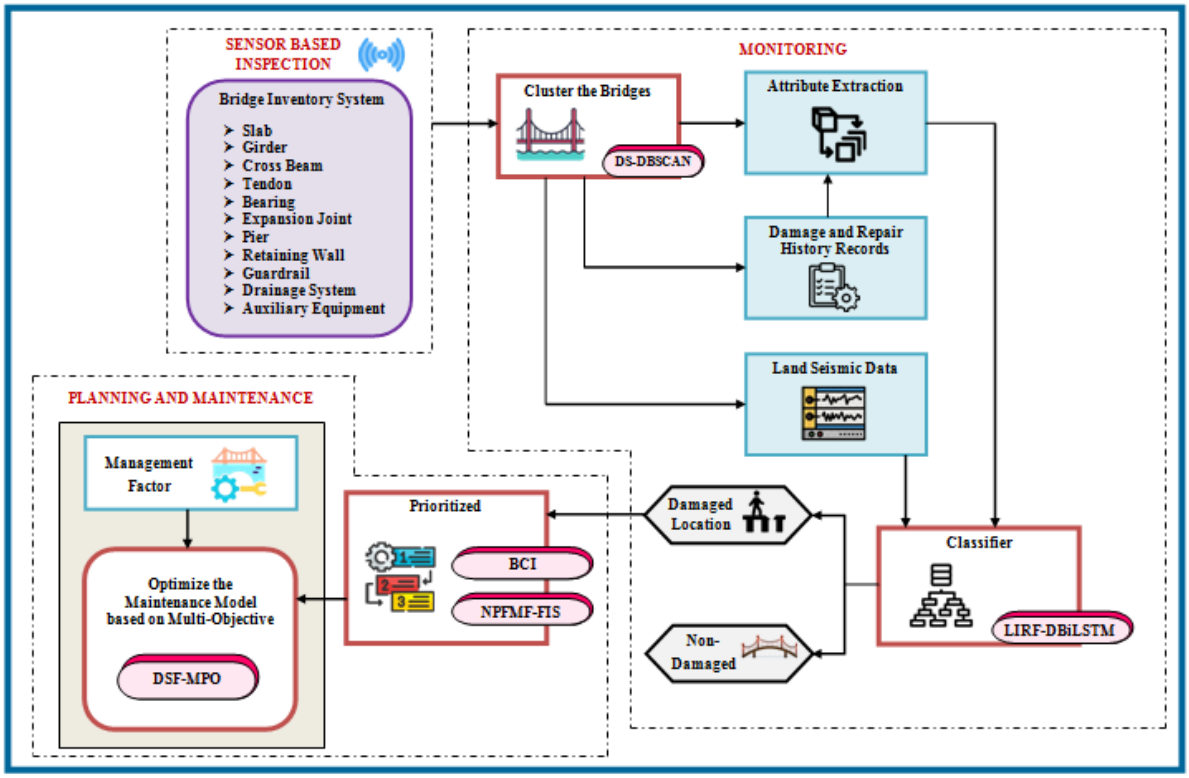


Figure 1: Block diagram for the proposed methodology

3.1 Sensor-based inspection

Initially, the sensor-based inspection is performed. From the bridge inventory system, the data is received. The data has a slab, girder, and other parts of the bridge. The gathered data is articulated as,

$$\wp_B = \{\wp_1, \wp_2, \wp_3, ..., \wp_n\} \tag{1}$$

Where, the collected bridge dataset is implied as $\wp_B$, and the n-number of gathered data is exemplified as $\wp_n$.

3.2 Monitoring

Here, with the aid of the attributes of the bridge inventory system, the sensed data are monitored.

3.2.1 Cluster the bridges

In this phase, since cost maintenance is different for diverse bridges, the bridge types are clustered as per their inventory system. The clustering process is carried out by the DS-DBSCAN, which supports the different density and shape-based functions. But, the traditional Density-Based Spatial Clustering of Applications with Noise (DBSCAN) struggles with clusters of similar density. Therefore, the delta score is utilized in this research method. Primarily, the delta score δ_s is computed for $\wp_B$, which is articulated as,

$$\delta_s = \frac{\omega_{\min} - \omega_{\max}}{\alpha(\omega_{\min}) - \alpha(\omega_{\max})} \tag{2}$$

Here, the minimum and maximum values of $\wp_B$ are notated as $\omega_{\min}$ and $\omega_{\max}$, and the average of $\omega_{\min}$ is signified as $\alpha(\omega_{\min})$, and the average of $\omega_{\max}$ is implied as $\alpha(\omega_{\max})$. Afterward, to find neighbor points, the distance λ_{dis} is computed between δ_s, which is expressed as,

$$\lambda_{dis} = \sqrt{(\delta_{s+1} - \delta_s)^2} \tag{3}$$

Next, check all the points are clustered. A new cluster will be created if all the points are not clustered. The procedures are repeated till the $\wp_B$ is grouped. The pseudocode for DS-DBSCAN is provided as follows,

Pseudocode: DS-DBSCAN

Input: $\wp_B$
Output: $\Re_y$

Begin
Initialize δ_s, λ_{dis}
For each $\wp_B$ do
Calculate $\delta_s = \frac{\omega_{\min} - \omega_{\max}}{\alpha(\omega_{\min}) - \alpha(\omega_{\max})}$
Calculate λ_{dis}
End for
If $(\wp_B == grouped)\{$

Terminate

}else {

Take further iteration

}end if

End

$\Re_y$ exemplifies the clustered bridge type.

3.2.2 Damage and repair history records

In this phase, damaged and repair history records are gathered from the $\Re_y$. In equation (4), the collected record set $\Im_R$ is mathematically denoted as,

$$\Im_R = \{\Im_1, \Im_2, \Im_3, ..., \Im_n\} \tag{4}$$

Where, the n-number of gathered records is notated as $\Im_n$.

3.2.3 Attribute extraction

In this phase, the attributes are extracted from $\Re_y$ and $\Im_R$. The attributes, namely length, width, depth, concrete, steel, and so on are extracted from $\Re_y$. The attributes, such as exposed reinforcement, efflorescence, damaged surface, and so on are extracted from $\Im_R$. κ_l indicates the extracted attribute.

3.2.4 Land seismic data

To reduce the misclassification performance during misclassification prediction, the land seismic data is extracted from the nearby bridge. λ_s illustrates the collected seismic data.

3.2.5 Classification

Here, for the identification of damage, κ_l and λ_s are provided as input to the LIRF-DBiLSTM since the input data is the time series data. Nevertheless, owing to the parameters, the traditional Deep Bidirectional Long Short Term Memory (DBiLSTM) has a higher computational issue. By using the Linear Interpolated Ridge Function (LIRF), the parameters are corrected in this research. Figure 2 displays the structure for LIRF-DBiSTM.

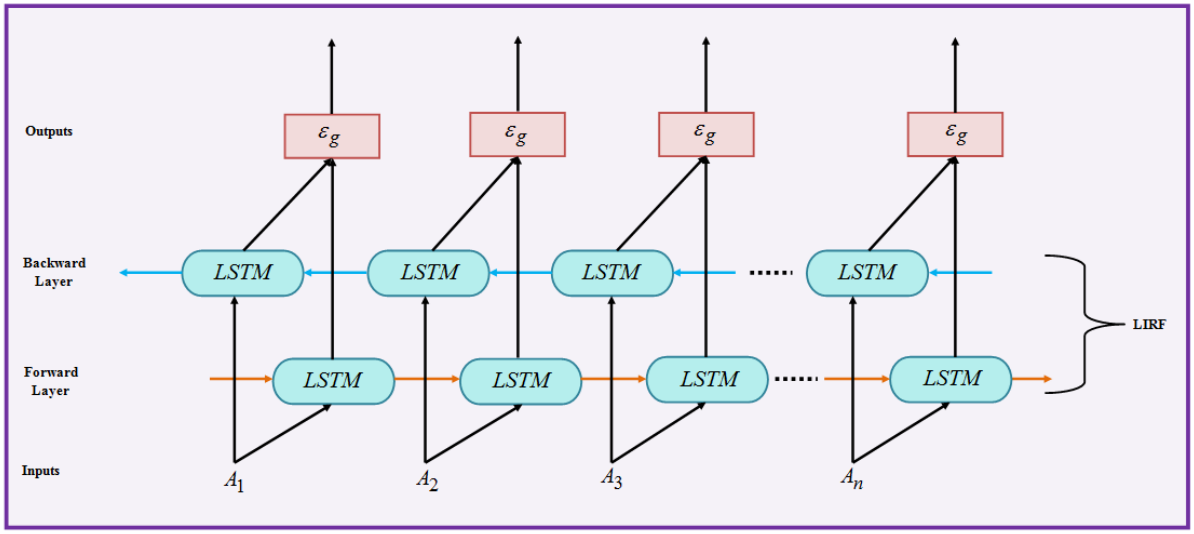


Figure 2: Structure for LIRF-DBiLSTM

Initially, A_x implies the combination of κ_l and λ_s. Subsequently, the forget gate μ_g is derived; in addition, the derivation is given in equation (5) as,

$$\mu_g = Act\left(\nu_f \left[\eta_{g-1}, A_x\right] + \upsilon_f\right) \tag{5}$$

Here, the activation function is exemplified as Act, and η_{g-1} denotes the output of the last layer. In this, to correct the parameters for the further process, the LIRF L_{irf} is utilized in the forget gate and is mentioned as,

$$L_{irf} = \sum L_{\text{int}}\left(\nu_f, \upsilon_f\right) + \ell \sum \rho \tag{6}$$

Where, the linear interpolation function is notated as $L_{\text{int}}(\ )$, the hyperparameter is signified as ℓ, and the penalty term is implied as ρ. Then, in equation (7), the expression for the input gate is provided as,

$$\chi_g = Act\left(\nu_i \left[\eta_{g-1}, A_x\right] + \upsilon_i\right) \tag{7}$$

$$K_g = \tanh\left(\chi_g\right) \tag{8}$$

Here, the cell state is represented as K_g. Finally, in equations (9) and (10), the activation function of the output layer ε_g is derived as,

$$\varepsilon_g = Act\left(\nu_o \left[\eta_{g-1}, A_x\right] + \upsilon_o\right) \tag{9}$$

$$\eta_{g-1} = \varepsilon_g * \tanh\left(K_g\right) \tag{10}$$

Where, the weight and bias value of the forget gate, input gate, and output gate are signified as $\left(\nu_f, \upsilon_f\right)$, $\left(\nu_i, \upsilon_i\right)$, and $\left(\nu_o, \upsilon_o\right)$, respectively. The forward and backward processes are

carried out in this DBiLSTM. Two types of output classes are presented (i.e.) damaged with location and non-damaged bridge.

3.3 Planning and Maintenance

Here, if the ε_g is damaged, then make planning for the maintenance.

3.3.1 Prioritization

The BCI is computed for the damaged structure. By evaluating and rating every single individual component of the structure, the BCI is calculated for determining the current value. If BCI is 100, then it is excellent; also, the lower levels are specified as low and medium categories. By utilizing NPFMF-FIS, the rule is generated for the prioritization grounded on the BCI. This is because encoding a priori knowledge is eased by the traditional Fuzzy Inference System (FIS). The conventional Membership Function (MF) in FIS has an unbalanced issue in controlling the parameters of the curve, thus affecting the performance of the rule generation. Hence, Normalized Pi-Functional Membership Function (NPFMF) is used in this research. Initially, the rule $\hbar$ is generated and is provided in equation (11) as,

$$\hbar = \begin{cases} 1^{st}\ planning, & if\ BCI < 30 \\ 2^{nd}\ planning, & if\ BCI < 60 \\ 3^{rd}\ planning, & otherwise \end{cases} \tag{11}$$

After that, $\hbar$ is transferred into crisp data $C(\hbar)$ at fuzzification time; in addition, the NPFMF M_{fun} is computed for the particular crisp data.

$$M_{fun} = \prod \left(C(\hbar), [N_{pa}] \right) \tag{12}$$

Here, the normalized controlled parameters are notated as N_{pa}. Next, $C(\hbar)$ is transferred into $\hbar$; also, the planning is scheduled centered on the equation (11).

3.3.2 Management

In this phase, management factors like painting, cleaning, crack replacement, grass and debris cleaning, and other maintenance factors are derived for $\hbar$. Therefore, to obtain a superior management process, the factors ψ_{ft} are optimized by utilizing DSF-MPO. This is because all the prey-centric location updation procedures are considered by the traditional Marine Predator Optimization (MPO). However, the stepsize movement is not considered dynamic, thus increasing the poor convergence rate. Therefore, for enhancing the convergence, the Dynamic Stepsize Function (DSF) is used in this research method. Initially, ψ_{ft} are considered as marine predators; in addition, the population position is randomly initialized.

$$Z = Z_{low} + \varphi \left(Z_{upp} - Z_{low} \right) \tag{13}$$

Where, the initialized population position is signified as Z, the lower and upper bound for variables are notated as Z_{low} and Z_{upp}, respectively, and φ indicates a random number. Thereafter, the fitness function is assessed. Here, minimum cost C_T and minimum user delay U_D are considered as the fitness function τ_{fit}.

$$\tau_{fit} = \min\left(U_D, C_T\right) \tag{14}$$

Then, grounded on three conditions, the population position is updated. When $\beta < 1/3\ \beta_{\max}$, the updation expression is provided as,

$$\aleph_i^{step} = R_v \otimes \left(\lambda_i - R_v \otimes q_i\right), i = 1,2,....,v \tag{15}$$

$$\aleph_i^{step(D)} = \left(Z_{upp} - Z_{low}\right) \times \frac{\beta_{\max} - \beta}{\beta_{\max}} + Z_{low} \tag{16}$$

$$q_i = \lambda_i + \zeta . R_v \otimes \aleph_i^{step} \otimes \aleph_i^{step(D)} \tag{17}$$

Here, the step size is implied as $\aleph_i^{step}$, a vector of random numbers is signified as R_v, the elite function is notated as λ_i, the prey is represented as q_i, the dynamic step size is indicated as $\aleph_i^{step(D)}$, the maximum iteration is exemplified as $\beta_{\max}$, the iteration count is signified as β, and ζ denotes a constant value. While $\beta < 1/3\ \beta_{\max} < \beta < 2/3\beta_{\max}$, the expression is given as,

$$\aleph_i^{step} = R_v \otimes \left(\lambda_i - R_v \otimes q_i\right),\ i = 1,2,...,v/2 \tag{18}$$

$$q_i = \lambda_i + \zeta . R_v \otimes \aleph_i^{step} \otimes \aleph_i^{step(D)} \tag{19}$$

When $I_r > 2/3\ M\left(I_r\right)$, the expression is provided as,

$$\aleph_i^{step} = R_v \otimes \left(\lambda_i - R_v \otimes q_i\right),\ i = 1,2,...,v \tag{20}$$

$$q_i = \lambda_i + \zeta . \varsigma \otimes \aleph_i^{step} \otimes \aleph_i^{step(D)} \tag{21}$$

Here, the adaptive control parameter is signified as ς. The pseudocode for the DSF-MPO is depicted as follows,

Pseudocode: DSF-MPO

Input: ψ_{ft}
Output: $\left(\psi_{ft}\right)_{opt}$

Begin
Initialize population, β, and $\beta_{\max}$
Calculate τ_{fit}
Set $\beta = 1$
While $\left(\beta \le \beta_{\max}\right)$ **do**
if $\beta < 1/3\ \beta_{\max}$ **{**
Updationby $q_i = \lambda_i + \zeta . R_v \otimes \aleph_i^{step} \otimes \aleph_i^{step(D)}$
} else {

Change population count
}**end if**
End while
End

$(\psi_{ft})_{opt}$ notates the optimized factors. The maintenance process is performed centered on $(\psi_{ft})_{opt}$. The performance of the research is investigated in the next section.

4. RESULT AND DISCUSSION

Here, the proposed method's performance is investigated; in addition, the proposed model is employed in the working platform of MATLAB.

4.1 Dataset description

The NBI dataset, which is publically available, is utilized in this research method for the performance analysis; in addition, the reference link is provided under the reference section. From geological locations, the land seismic data is obtained. From the data, 80% is utilized for training purposes; also, for testing purposes, the remaining 20% is used.

4.2 Performance analysis

(a) Performance analysis for the clustering process

Here, the DS-DBSCAN's performance is investigated with the prevailing DBSCAN, K-Means (KM), Gaussian Mixture Model (GMM), and Fuzzy C-Means (FCM) algorithm.

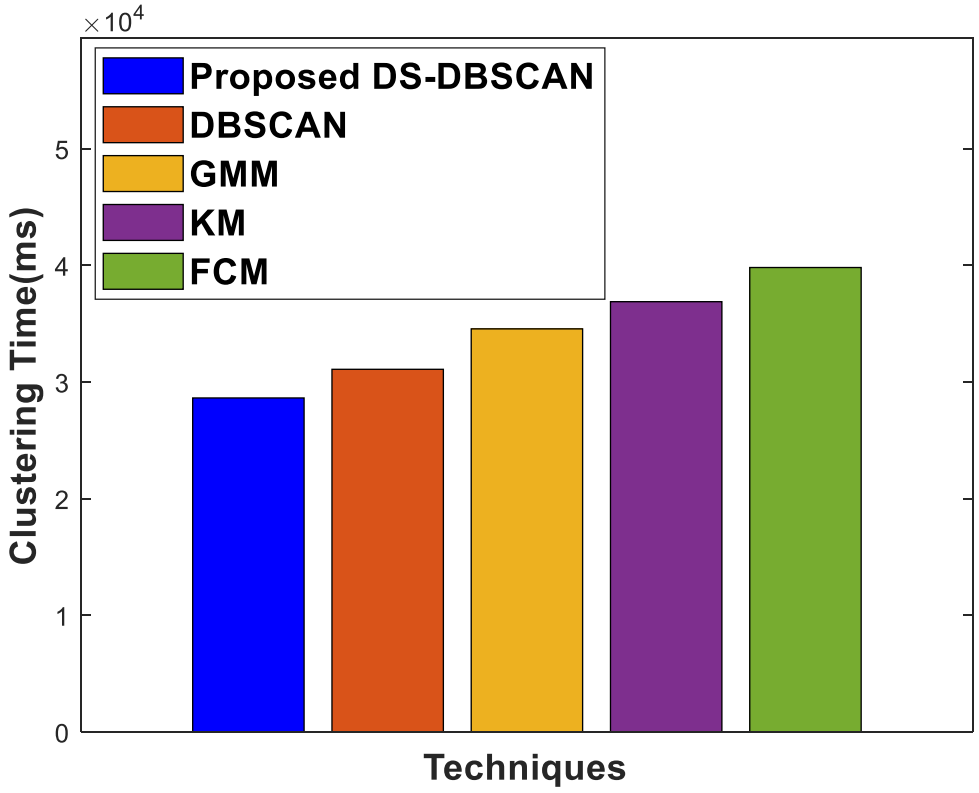


Figure 3: Clustering time analysis

The clustering time analysis of the presented clustering framework is analogized with the existing approaches, which is graphically plotted in Figure 3. Since a similar density group issue is solved by the DS function, DS-DBSCAN attains a lower clustering time. 34203ms is the average clustering time of the prevailing approaches.

(b) Performance analysis for the classification process

Here, the proposed LIRF-DBiLSTM is compared with the prevailing DBiLSTM, ANN, Long Short Term Memory (LSTM), and Recurrent Neural Network (RNN).

Table 1: Error analysis

Metrics	Proposed LIRF-DBiLSTM	DBiLSTM	LSTM	RNN	ANN
MSE	1.6	4.6	7.5	9.2	12
MAE	2.3	4.1	6.9	8.4	11.3
RMSE	1.3	3.1	6.2	10.5	12.8

In Table 1, the error analysis of the classifiers grounded on Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Square Error (MSE) is depicted. The MSE, MAE,

and RMSE values of LIRF-DBiLSTM are 1.6, 2.3, and 1.3, correspondingly; however, when compared to the proposed framework, the prevailing algorithms have higher error rates.

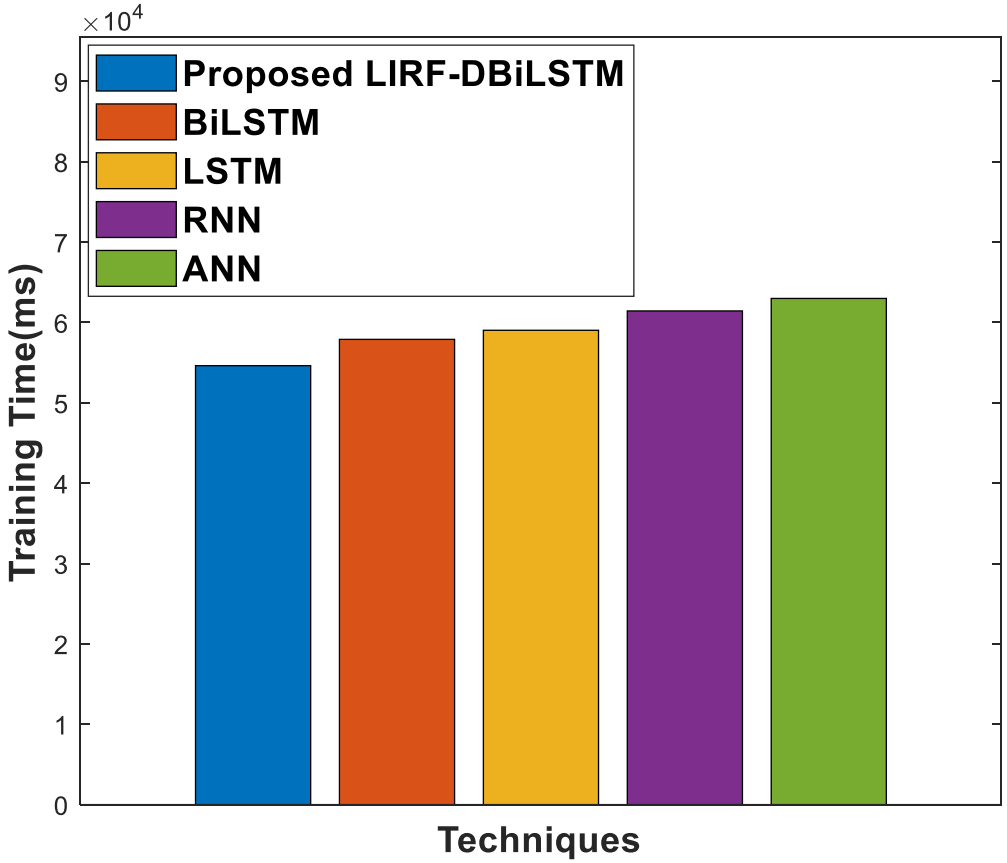


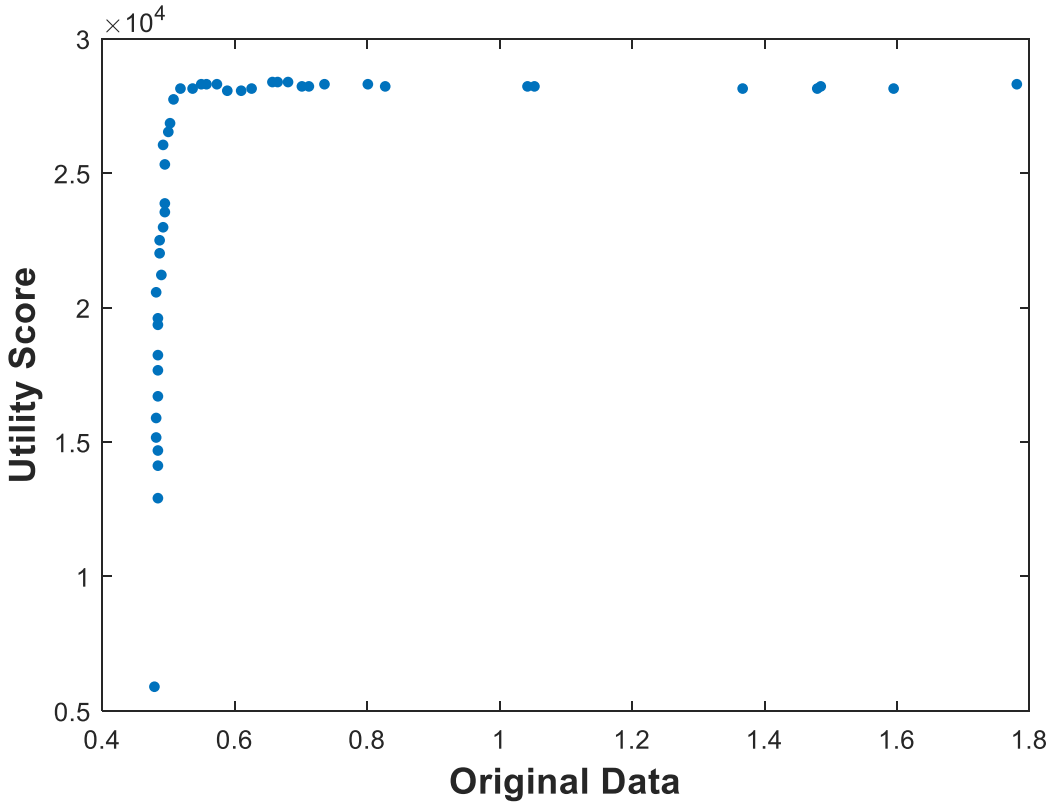
Figure 4: Graphical representation of training time analysis

The training time analysis is graphically plotted and is shown in Figure 4. 54621ms is taken by the LIRF-DBiLSTM for training the data, which was lower when contrasted with the other methods due to considering LIRF. 60333ms is the average training time of the prevailing approaches.

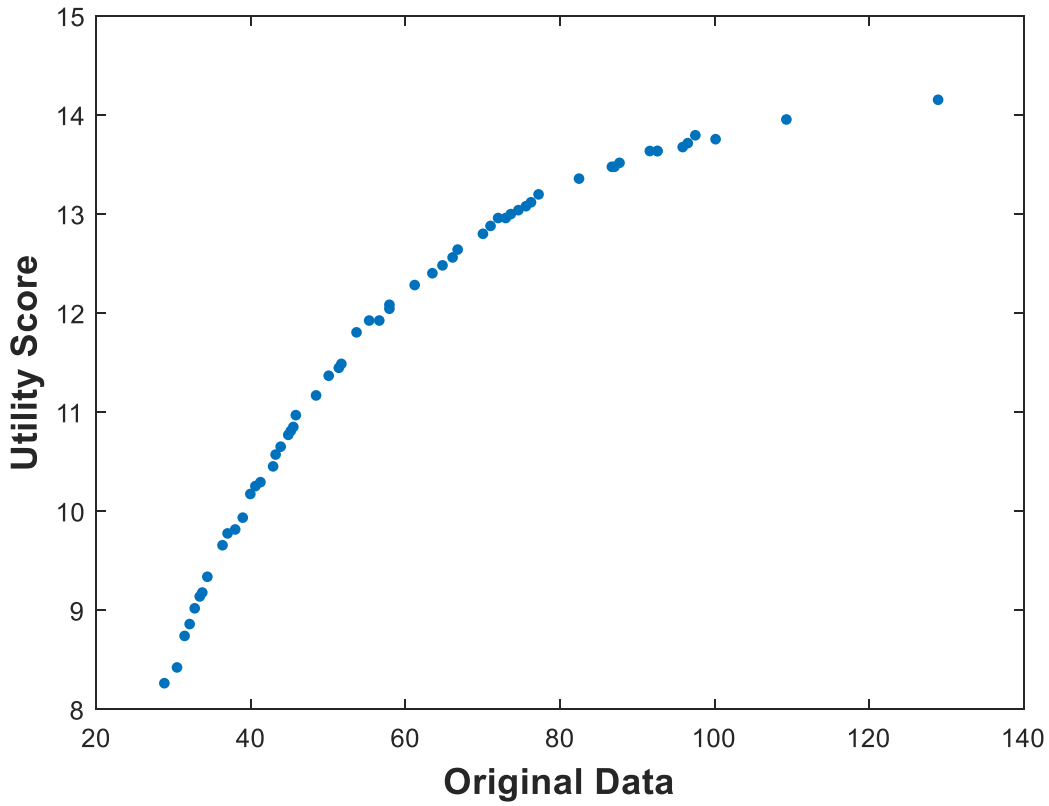
Table 2: Performance analysis of LIRF-DBiLSTM with the other classifiers based on statistical measures

Measures	Proposed LIRF-DBiLSTM	DBiLSTM	LSTM	RNN	ANN
Accuracy	98.96	96.2	93	92	90
Precision	97	94.5	91.2	90.3	88.6
Recall	96	94	92	90	89
F-Measure	96.5	94.25	91.6	90.15	89.1

In Table 2, the performance analysis of the classifiers centered on the recall, precision, accuracy, and F-measure metrics is depicted. Owing to the inclusion of the LIRF function, the LIRF-DBiLSTM obtains a higher accuracy of 98.96% and an F-measure of 96.5%. However, when compared to the proposed approach, lower performance was attained by the prevailing method.



(a)



(b)

Figure 5: Utility plot for (a) maintenance cost and (b) user delay rate

The utility plot is depicted in Figure 5. The maintenance cost is raised above $2.5X10^4$ for the proposed approach-centric BMS in Figure 5 (a). In Figure 5 (b), concerning the original data, the user delay rate of the proposed method is raised. Therefore, it indicates that the presented approach is highly helpful for the BMS.

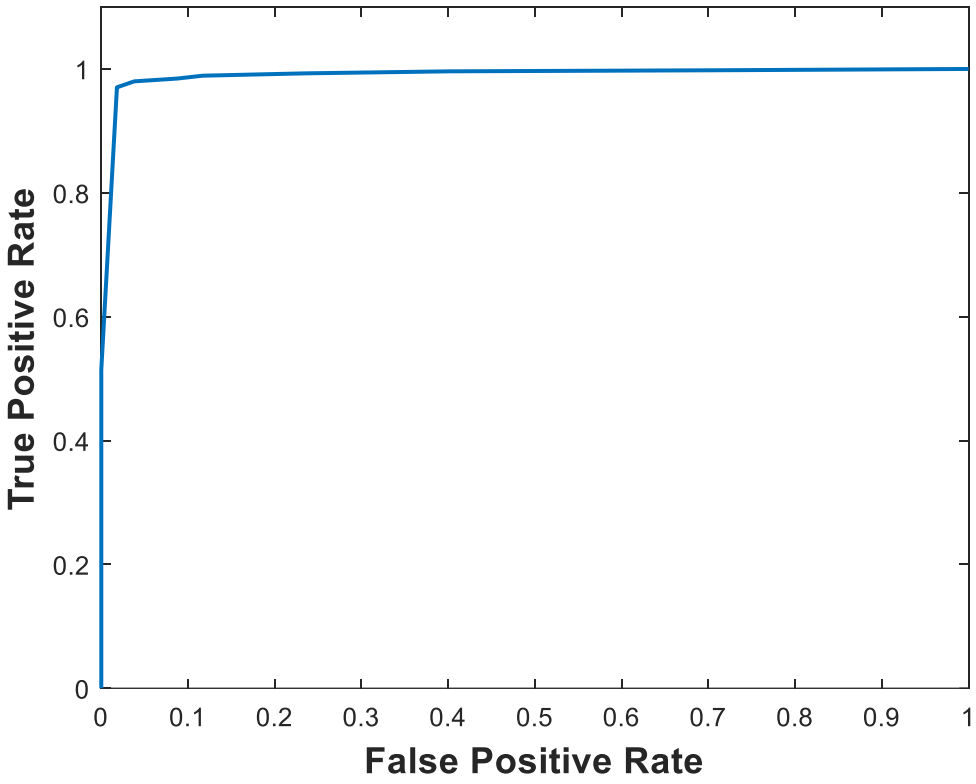


Figure 6: ROC analysis

The Region of Curve (ROC) plot of the proposed framework is shown in Figure 6. The true positive rate reaches nearly 1. Hence, it is concluded that higher performance is achieved by the proposed method in the BMS.

(c) Performance analysis for the prioritization process

In this phase, the proposed NPFMF-FIS's performance is investigated with the prevailing FIS, Decision Rule (DR), Trapezoidal Fuzzy Logic (TFL), and Sigmoid Fuzzy Logic (SFL).

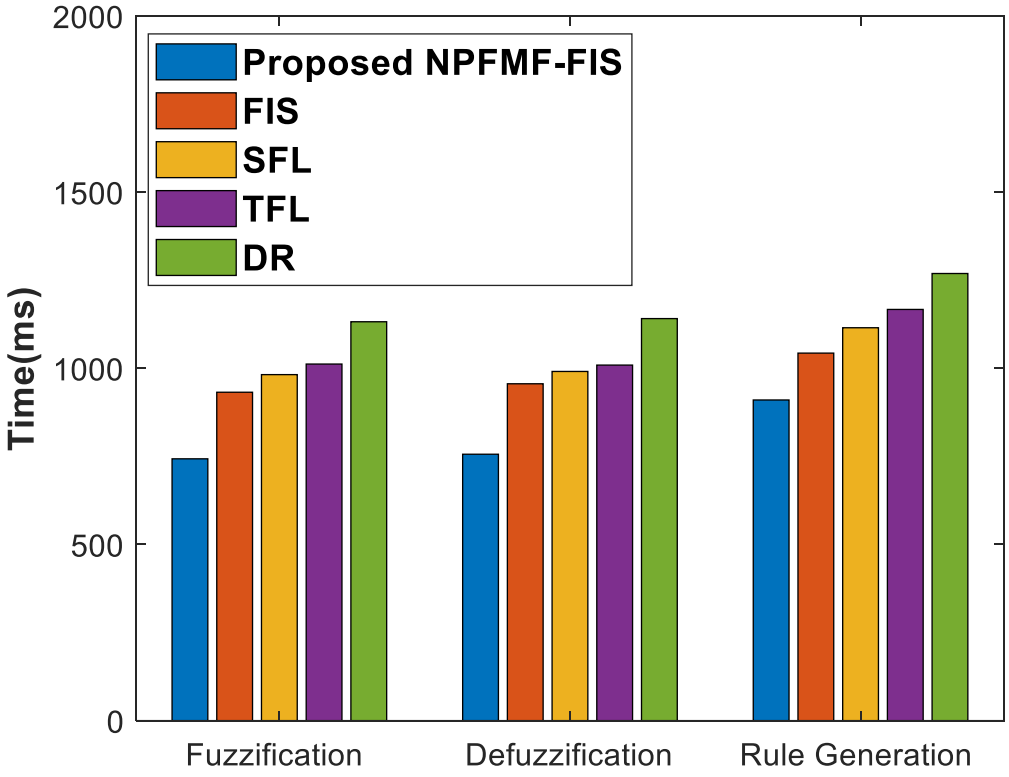


Figure 7: Graphical plot of performance analysis of the prioritization process

The fuzzification time, defuzzification time, and rule generation time of the proposed NPFMF-FIS are compared with the prevailing approaches. Here, 743ms, 756ms, and 910ms are the fuzzification, defuzzification, and rule generation times of the NPFMF-FIS, correspondingly. Nevertheless, more time was taken by the existing approaches. Due to the inclusion of NPFMF, superior performance is obtained by the proposed framework.

(d) Performance analysis for factors optimization

In this phase, the proposed DSF-MPO is analogized with Aquila Optimization (AO), Emperor Penguin Optimization (EPO), MPO, and Sun Flower Optimization (SFO) algorithms.

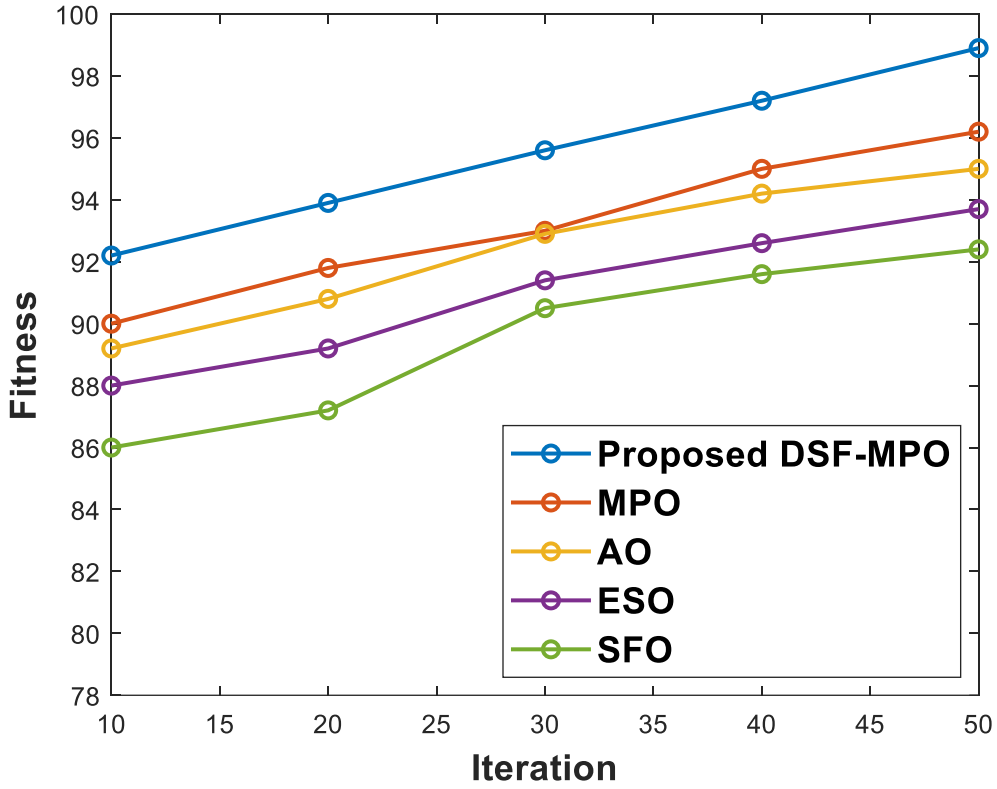


Figure 8: Fitness Vs Iteration Analysis

Figure 8 depicts the fitness Vs iteration analysis. The fitness percentage of the DSF-MPO is 93.9 while the iteration count is 20. However, when contrasted with the proposed method, prevailing approaches have lesser fitness for the same iteration count. This is because the proposed framework solves the poor convergence issue by using DSF.

4.3 Comparative analysis

Table 3: Comparative analysis

Author Name	Methods used	Accuracy	Precision	Recall
(Jaafaru&Agbelie, 2022)	ML model with multi-criteria decision analysis	84%	-	-
(Fang et al., 2023)	Multiple ML model assessment	82.42%	84%	86%
(Corbally&Malekjafarian, 2024)	Deep learning model	93.31%	-	-
(Cardellicchio et al., 2023)	Different deep-learning approaches	63.46%	78.68%	55.42%
(Ye et al., 2023)	Random Forest (RF)	92.5%	-	-
Proposed	LIRF-DBiLSTM	98.96%	97%	96%

In Table 3, the comparative analysis with the top-notch works grounded on accuracy, precision, and recall metrics is shown. Higher performance is attained by the proposed method centered on all the metrics. A higher accuracy of 93.31% was obtained by the prevailing deep learning model, which was also lower when contrasted with the proposed approach-centric BMS. Therefore, it indicates that when analogized with top-notch works, higher performance is attained by the proposed framework based on BMS.

5. CONCLUSION

In this paper, a LIRF-DBiLSTM-centric BMS is proposed. Three functions, namely sensor-based inspection, monitoring, as well as planning and maintenance are mainly considered in the proposed methodology. The NBI dataset is utilized by the proposed method for the performance analysis. The performance of the proposed research is analogized with the prevailing research approaches. When contrasted with the prevailing approaches, an accuracy of 98.96% with less training time was obtained by the proposed LIRF-DBiLSTM. Furthermore, higher performance was attained by the proposed approach-centric BMS in comparison with the top-notch work. Moreover, the maintenance cost and user delay rate are reduced, which is observed from the utility plot. But, this research only considers the cost and delay rate as the objective function.

Future scope: The proposed BMS will be improved in the future by considering more number of objective functions with advanced approaches.

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Dataset: https://www.fhwa.dot.gov/bridge/snbi.cfm

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