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Baojia Gong[1*]

Structural Strength of Corrugated Steel Web Box Beam Based on Finite Element Analysis

Abstract: - Deflection prediction in composite box-girder bridges with corrugated steel webs may be limited in a number of ways. Accurately predicting the complicated behaviour of such structures, including the intricate interaction of diverse materials and geometries, can be difficult and may result in inaccurate predictions. To overcome these issues, in this manuscript Structural Strength of Corrugated Steel Web Box Beam Based on Finite Element Analysis (SS-CSWBB-RBAGCN)is proposed. Originally, the Structural Defects Network (SDNET) 2018 dataset is used to gather the input data. Then, the collected data is fed into pre-processing utilizingSurface Normal Gabor Filter (SNGF).SNGF is used for data cleaning and to find missing values. Then the preprocessed data are given to Relational Bilevel aggregation graph convolutional network(RBAGCN) for predicting deflection behavior of the bridge structure. In general, RBAGCN does not express adapting optimization strategies to determine optimal parameters. Hence, the Tyrannosaurus Optimization Algorithm (TOA) to optimize which accurately predict the deflection behavior of the bridge structure. The proposed SS-CSWBB-RBAGCN method covers 29.36%, 23.27% and 26.42% higher accuracy, 18.46%, 20.38% and 15.45% lower Absolute Percentage Error and 18.26%, 28.41% and 29.41% higher Determination Coefficient compared with existing methods such as, Optimizing Shear Capacity Prediction of Steel Beams with Machine Learning Techniques (SCP-SB-XGB), Prediction analysis of deflection in the construction of composite box-girder bridge with corrugated steel webs based on MEC-BP neural networks(DCCBGB-CSW-BPNN), and Utilizing Artificial Intelligence Approaches to Determine the Shear Strength of Steel Beams with Flat Webs (AI-SSSB-CFBNN)respectively.

Keywords: Relational Bi-level Aggregation Graph Convolutional Network, Surface Normal Gabor Filter, Steel Web Box BeamandTyrannosaurus Optimization Algorithm.

I. INTRODUCTION

The box girders with corrugated steel webs (CSWs) have become popular in bridge building due to their ability to reduce weight when compared to concrete webs (CWs). A wider girder span, improved anti-seismic performance, and the complete elimination of web cracking are just a few advantages that the CSWs-PC rigid frame bridge has over traditional prestressed concrete rigid frame bridges. [1–5]. Nevertheless, the shear deformation of CSWs would raise the main girder's deflection as their shear stiffness is lower than that of CWs. [6]. During the construction process, which can have some unfavourable impacts. The structural strength of bridges is critical to their safety and lifespan, especially under dynamic loading situations and changing environmental circumstances [7-9]. Corrugated steel web box beams have developed as a viable structural solution due to their lightweight construction, high strength-to-weight ratio, and corrosion resistance [10-13]. However, there is still a need to fully understand and improve their structural performance in order to full fill the increasingly stringent standards of modern infrastructure projects. In response to this necessity, this research investigates the structural strength of corrugated steel web box beams using finite element analysis (FEA) [14-16]. This work tries to understand the complex mechanical behavior of such beams under various loading scenarios, including static and dynamic loads, as well as environmental influences [17]. Through rigorous analysis and simulation, the project seeks to enhance our understanding of the key factors influencing the structural strength of corrugated steel web box beams and provide valuable insights for optimizing their design and construction practices [18]. In order to maintain structural integrity and safety during the building process, predicting deflection is an essential task in bridge engineering for CSWs [19].

The potential limitation of this research's findings to be applied to other bridge construction projects is one of its drawbacks. The case investigation of a CSWs is the main topic of the research. This type of bridge may have special features and construction difficulties that are not typical of other bridge types. There may be issues with scalability and adaptation to various bridge designs or building techniques if a high-fidelity finite element model is used exclusively for data creation and validation. Furthermore, the neural network-based prediction method's

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[1] 1*College of Civil Engineering, Lanzhou Jiaotong University, Lanzhou, Gansu, 730070, China

1*Email: baoijagong550@gmail.com

complexity and the finite element model's time-consuming parameter adjustments could make it impractical for use in real-time construction scenarios.

To address the challenges given by complex structural interconnections and dynamic loading circumstances, this SS-CSWBB-RBAGCN model provides a new approach based on Tyrannosaurus Optimization Algorithm (TOA)and Relational Bilevel aggregation graph convolutional network (RBAGCN). Bridge engineering has advanced significantly with the creation of CSWs, which offer a combination of structural efficiency, longevity, and visual appeal. However, maintaining the structural integrity of these bridges during the construction process is critical to their long-term performance and safety. Deflection, in particular, is an important element that influences the structural behavior and functionality of bridges. As a result, SS-CSWBB-RBAGCN high accurate prediction and analysis of deflection during construction are critical for optimizing design, building methods, and material utilization.

Below is a summary of this research work's principal contributions.

- In this research, Structural Strength of Corrugated Steel Web Box Beam Based on Finite Element Analysis (SS-CSWBB-RBAGCN) is proposed.
- Originally the input data is collected from the SDNET 2018 dataset.
- The proposed SS-CSWBB-RBAGCN method integrates multiple advanced techniques, including Surface Normal Gabor Filter (SNGF) for preprocessing.
- Then the preprocessed given to Relational Bilevel aggregation graph convolutional network (RBAGCN)for predicting deflection behavior of the bridge structure.
- Unlike traditional RBAGCN approaches, which lack optimization methods for computing optimal parameters, the proposed method incorporates Tyrannosaurus Optimization Algorithm (TOA).TOA optimizes the weight parameters of RBAGCN.
- The proposed model's effectiveness is evaluated using current techniques, including as DCCBGB-CSW-BPNN, SCP-SB-XGB and AI-SSSB-CFBNN models respectively.

The remaining manuscripts are arranged as follows: The literature review is reviewed in Part 2, the technique is explained in Part 3, the results are proven in Part 4, and the document is concluded in Part 5..

II. LITERATURE SURVEY

Wang et al. [20] have presented an “Prediction analysis of deflection in the construction of composite box-girder bridge with corrugated steel webs based on MEC-BP neural networks”. The balanced cantilever technique is an effective computational framework for predicting deflection in a PC rigid frame bridge with CSWs. The framework consists of three stages of analysis: first, gather the datasets needed to establish the prediction model. The high-fidelity three-dimensional finite element model and the Latin hypercube sampling approach produced the input samples and output response in these datasets, respectively. Next, an optimised neural network model that combines with the mind evolutionary computing method and the back-propagation algorithm was developed utilising the datasets. Both low precision and high accuracy are offered.

Elamary et al. [21] have presented an “Optimizing Shear Capacity Prediction of Steel Beams with Machine Learning Techniques”. Steel beams' shear capability was crucial for a building project's safe and effective design. The plate girders' maximum shear resistance has not been reliably predicted by previous methods; nevertheless, machine learning has surfaced as a novel strategy to tackle this problem. The scikit-learn library's XGB regressor model outperforms the other ML methods. It offers poor precision and low MAE.

Mohamed et al. [22] have presented an “Utilizing Artificial Intelligence Approaches to Determine the Shear Strength of Steel Beams with Flat Webs”. Shear strength of steel beams was shown to be one of the most significant determinants of how rapidly webs buckle. The current methods did not reach the required dependability to estimate the plate girders' maximum shear resistance girders, despite substantial research being conducted over the preceding three decades. The last several years have seen the introduction of new methods known as Learner Techniques, which were used to ascertain the steel beams' shear strength. It has a low determination coefficient and good sensitivity.

Zhao et al. [23] have presented anFlexural performance of precast segmental CSWs ..Precast segmental continuous box girders with corrugated steel webs were an innovative technique to bridge construction that has several benefits, including faster construction, increased durability, and lower maintenance costs. Understanding the flexural performance of such structures was critical for maintaining their structural integrity and safety over time. The purpose of this literature analysis was to investigate and analyze existing research on this topic in order to get insight into the behavior of precast segmental CSWs under flexural loads. It provides high precision and low sensitivity.

Hassanein et al. [24] have presented an “Behavior and Design of Trapezoidally Corrugated Web Girders for Bridge Construction”. The emphases were on corrugated web girders' distinct structural features and potential advantages over typical bridge girder designs. Understanding the behavior and design concepts of these girders was important for improving bridge performance and sustainability. The behaviour and design of web girders with trapezoidal corrugation in bridge building techniques, findings, and conclusions were examined to discover patterns, problems, and areas for future research. It provides low MSE and low precision.

Chi et al. [25] have presented an “Radial Force Analysis of Long Span Bridge with Trapezoidally Corrugated Steel Webs”. The goals were to understand how radial forces were distributed and how they affect such systems. The significance and implications of radial force analysis for the design and performance of long-span bridges with trapezoidally corrugated steel webs. The survey begins with an overview of trapezoidally corrugated steel webs in long-span bridge construction, highlighting their unique structural qualities and advantages. The significance of radial force analysis in optimizing bridge design and ensuring structural integrity was emphasized. It provides low MSE and low accuracy.

Li and Zhou [26] have presented a “Natural frequency of prismatic and tapered composite girders with corrugated steel webs”. To present a complete overview of existing research on this topic, emphasizing the importance and consequences of natural frequency analysis in the design and assessment of CSWs. Natural frequency analysis was emphasized as an important tool for examining the dynamic response, vibration characteristics, and serviceability of these bridge systems under varied loading circumstances. Prismmatic and tapered CSWs were examined for their natural frequencies in order to shed light on the behaviour of dynamic loads and its effects on bridge performance. It provides high determination coefficient and low precision.

III. PROPOSED METHODOLOGY

In this section, Structural Strength of Corrugated Steel Web Box Beam Based on Finite Element Analysis (SS-CSWBB-RBAGCN) is proposed. The approach involves five steps: Data Acquisition, Pre-processing, prediction and optimization. Initially, the Structural Defects Network (SDNET) 2018 dataset is used to gather the input data. The gathered data is then sent into Surface Normal Gabor Filter pre-processing (SNGF). SNGF is used to locate missing values and clean up data. Next, RBAGCNM is trained using the preprocessed data to predict the deflection behavior of the bridge structure. Generally speaking, RBAGCN does not explain optimization algorithms that can be adjusted to find the ideal settings. As a result, the Tyrannosaurus Optimization Algorithm (TOA) was developed to optimize and precisely forecast the bridge structure's deflection behavior. Block Diagram of the proposed SS-CSWBB-RBAGCN is illustrated in figure 1

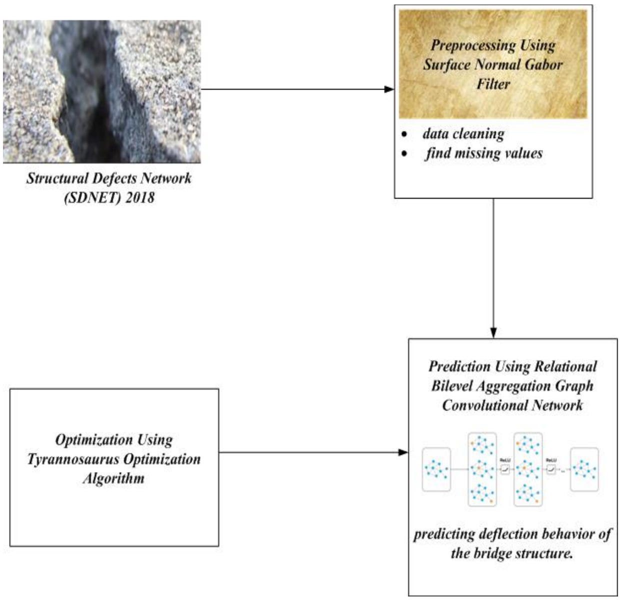

Figure 1: Block Diagram of SSO-CSWBB-FEA methods

A. Data Acquisition

Firstly, the input data's is collected from Structural Defects Network (SDNET) 2018 [27]. Concrete crack detection methods based on artificial intelligence are trained, validated, and tested using an annotated dataset named SDNET2018. More than 56,000 pictures of cracked and uncracked concrete walls, pavements, and bridge decks may be seen in SDNET2018. There are fissures in the dataset that are as wide as 25 mm and as tiny as 0.06 mm. Data featuring a range of impediments, like surface irregularities, scaling, shadows edges, holes, and background detritus, are also included in the dataset. SDNET2018 would be helpful for the development of deep learning convolutional neural network-based algorithms for concrete crack identification, which is an area of ongoing study in the field of structural health monitoring.

B. Pre-Processing Using Surface Normal Gabor Filter (SNGF)

In this section, Pre-Processing using Surface Normal Gabor Filter (SNGF) [28] is discussed. SNGF is used for data cleaning and to find missing values. Multistage analysis is made possible by SNGF, making it possible to identify deflection behavior at different scales. This is important because there are several levels of deflection patterns that bridge constructions can display, ranging from microscopic deformations to macroscopic movements. SNGF can efficiently capture these variations by applying Gabor filters at various scales. The surface normal' orientation has an impact on SNGF. Complex deformations along various orientations are frequently seen in bridge constructions as a result of various factors, including material qualities and load distribution. Due to its orientation sensitivity, SNGF is able to distinguish between these differences and offer more precise deflection behavior predictions.

$$g(x, y \mid \lambda, \theta, \psi, \sigma, \gamma) = \exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right)\exp\left[i\left(2\pi\frac{x'}{\lambda} + \psi\right)\right] \tag{1}$$

Here , λ denotes the sinusoidal wave's wavelength; θ denotes the oriented of the Gabor function; ψ denotes the Gabor Kernel's phase offset from its centre; γ represent the filter kernel's spatial aspect ratio; π represented the normalized surface topography; σ represent the standard deviation of the Gaussian envelop.

$$g_r(x, y) = \exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right)\cos\left(2\pi\frac{x'}{\lambda} + \psi\right) \tag{2}$$

Here , $g_r(x, y)$ represent the real part. ψ denotes the phase offset from the centre of the Gabor Kernel; γ represent the spatial aspect ratio of the filter kernel; π represented the normalized surface topography; σ represent the Gaussian envelope standard deviation. Data cleaning is determined in equation (3)

$$g_i(x, y) = \exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right)\sin\left(2\pi\frac{x'}{\lambda} + \psi\right) \tag{3}$$

Here, $g_i(x, y)$ represent the imaginary part. ψ denotes the phase offset from the centre of the Gabor Kernel; γ represent the spatial aspect ratio of the filter kernel; π represented the normalized surface topography; σ represent the Gaussian envelope standard deviation Missing value is determined in equation (4)

$$G_{C\cdot E}(x, y) = G_{C\cdot R}(x, y)^2 + G_{C\cdot I}(x, y)^2 \tag{4}$$

Here , $G_{C\cdot E}(x, y)$ represent the square of the output feature matrices is used to compute the gabor energy.. $G_{C\cdot R}(x, y)$ represent the actual feature matrix. $G_{C\cdot I}(x, y)$ represent the imaginary feature matrix.

$$G_{C\cdot E}(x, y) = \sum_{n=-i}^{i}\sum_{k=-i}^{i}\left[f_q(l, k)\cdot m_V(x+l, y+k) - fh(l, k)\cdot m_X(x+l, y+k)\right] \tag{5}$$

Here $G_{C\cdot E}(x, y)$ represent the Gabor energy; $m_V(x, y)\, and\; m_X(x, y)$ is specifies the surface normal vector; x, k and l represent the kernel window's indices. Finally the SNGF cleaned and find missing values of the data. Then the pre-processed data are given to RBAGCN for prediction.

C. Prediction Using Relational Bilevel Aggregation Graph Convolutional Network (RBAGCN)

In this segment, Prediction Using RBAGCN [29] is discussed. RBAGCN is used for predicting deflection behavior of the bridge structure. Relational learning approaches are used by RBAGCN to capture intricate interactions between structural elements. The complex interdependencies among different parts found in bridges are influenced by a variety of factors, including material qualities, structural design, and load distribution. By taking into account the complex interactions within the bridge system, RBAGCN's modeling of these relationships allows for more precise deflection predictions. The architecture and learning processes of RBAGCN are specifically designed to accurately predict deflection behavior.

$$E_l^y = \left[\overset{\rightarrow}{LSTM}\left(x_l^y, \overset{\rightarrow}{E_{l-1}^y}\right)\right] \tag{6}$$

Where. $\overset{\rightarrow}{LSTM}$, denoted the network encodes contextual information for all modality and E_l^y represent context-independent arbitrary modality with raw feature representation for utterances $l \; and \; y$.

$$S(o) = (\{G_c(o), F_c(o)\}) \tag{7}$$

Where $G_c(o)$ represents connected neighbourhood at graph, $F_c(o)$ denotes disconnected neighbourhood at graph.

$$G_c(o) = \{r \mid r \in H, (r,o) \in K \tag{8}$$

Where r,o represented as the similarity metric function, K represented as modify the simulated nodes collected at the first layer with the desired node. H , denoted as matching resemblance.

$$F_c(o) = \{r \mid r \in H, (r,o) \notin K \tag{9}$$

Where $\notin K$ represented as modifying the un-simulated nodes collected at the second layer with the desired node, this is the greatest efficiency rating for RBAGCN in deflection and prediction.

$$s(r,o) = \left(1 - \frac{\arccos\,(sim(j_r, j_o))}{\pi}\right) \tag{10}$$

Where $sim\,(\cdot,\cdot)$ represent the cosine similarity function. j_r, j_o, indicate the characteristics of nodes r,o in the network, respectively. π, denotes the processing to design the textile based on deflection and detection in the identification corrugated steel web box beam were built with RBAGCN, and its computerized effectiveness was verified through observations. The deflection behavior of the bridge structure is predicted in equation (11)

$$\sigma^{(u)}(y) = \left(E^{(u)}\, y + v^{(u)}\right) \tag{11}$$

Where $\sigma^{(u)}$ represented according to the linear transformation function, u is a node that is in the clustered neighbourhood. $W^{(u)}$, is a weighted matrix, while y represents a node's attribute in the overall cluster neighbourhood. $v^{(u)}$, denotes the bias vector. Finally the RBAGCN predicted the deflection behavior of the bridge structure. In this research, “Tyrannosaurus Optimization Algorithm” is assigned to improve weight parameter of RBAGCN. In this case, the turning weight parameter of the RBAGCN is given to TOA.

D. Optimization Using Tyrannosaurus Optimization Algorithm (TOA)

In this section, optimization using Tyrannosaurus Optimization Algorithm (TOA) [30] is discussed. Here the proposed RBAGCN weight and bias parameters $G_c \; and \; E^{(u)}$ are optimized using TOA. For predicting deflection behavior in bridge structures, the Tyrannosaurus Optimization Algorithm (TOA) has a number of benefits. These include the ability to balance exploitation and exploration, carry out global search, converge rapidly, manage complexities and nonlinearities, exhibit robustness, and allow for parameter tuning. Because of these benefits, TOA is a viable method for improving the precision and effectiveness of deflection prediction models in applications related to bridge engineering.

Step 1: Initialization

The starting population of TOA is generated randomly. Then the initialization is derived in equation (12).

$$Y = \begin{bmatrix} y_{1,1} & \cdots & \cdots & y_{1,k} & y_{1,n-1} & y_{1,o} \\ y_{2,1} & \cdots & \cdots & y_{2,k} & \cdots & y_{2,o} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ y_{O-1,1} & \cdots & \cdots & y_{O-1,k} & \cdots & y_{O-1,o} \\ y_{O,1} & \cdots & \cdots & y_{O,k} & y_{O,o-1} & y_{O,o} \end{bmatrix} \tag{12}$$

Where, Y denotes the candidate solutions, $Y_{1,1}$ denoted the previous observation.

Step 2: Random Generation

Through TOA, the input fitness function acquired randomization upon initialization.

Step 3: Fitness Function

Based on the present best location, the initialised parameters are determined. Determine the fitness level of every person.

$$Fitness\ Function = optimizing\ [G_c\ and\ E^{(u)}\ ] \tag{13}$$

Where G_c denotes the high accuracy and $E^{(u)}$ denotes the low APE.

Step4: Hunting and Chasing G_c

In the forward pass, every node in the network that depends on an accessible link with available bandwidth receives the message from base node. The node sends the data packet to closest node till it reaches the target node after assessing the link state is randomly given in equation (14)

$$X_{new} = \begin{Bmatrix} x_{new} & if\ rand() < Er \\ Random & else \end{Bmatrix} \tag{14}$$

Here, Er denotes estimation of reaching scattered route; X_{new} is denotes the update the exploration position and x_{new} is denotes the target of the node position. T-Rex starts exploring, and then its location is given in equation (15)

$$G_c = x + rand() * sr * (tpos * tr - t\arg et * pr) \tag{15}$$

Here, x_{new} is denotes the target of the exploration position; sr is denotes the success rate of node; tr is denotes the target of the exploration node position; $tpos$ is denotes the position of the target node; pr signifies exploration position of node, x signifies random exploration position.

Step 5: Selection $E^{(u)}$

Applying other exploration methods, such mutation or crossover, to the chosen individuals would provide diversity to the selecting. By taking this stage, the algorithm can investigate several areas of the solution space without hastily converging to poor solutions defends itself during a node expedition. By contrasting the fitness function, it is realized. Thus it is given in equation (16)

$$E^{(u)} = \begin{Bmatrix} update\,the\,t\arg et\ position & if\ f(X) < f(X_{new}) \\ t\arg et\ is\ zero & otherwise \end{Bmatrix} \tag{16}$$

Here, X_i^{k+1} is denotes the fitness function of the exploration phase; $f(X)$ denotes fitness function of initial randomly route location, $f(X_{new})$ is denotes the fitness function for the update node location. Figure 2 shows the flowchart of TOA,

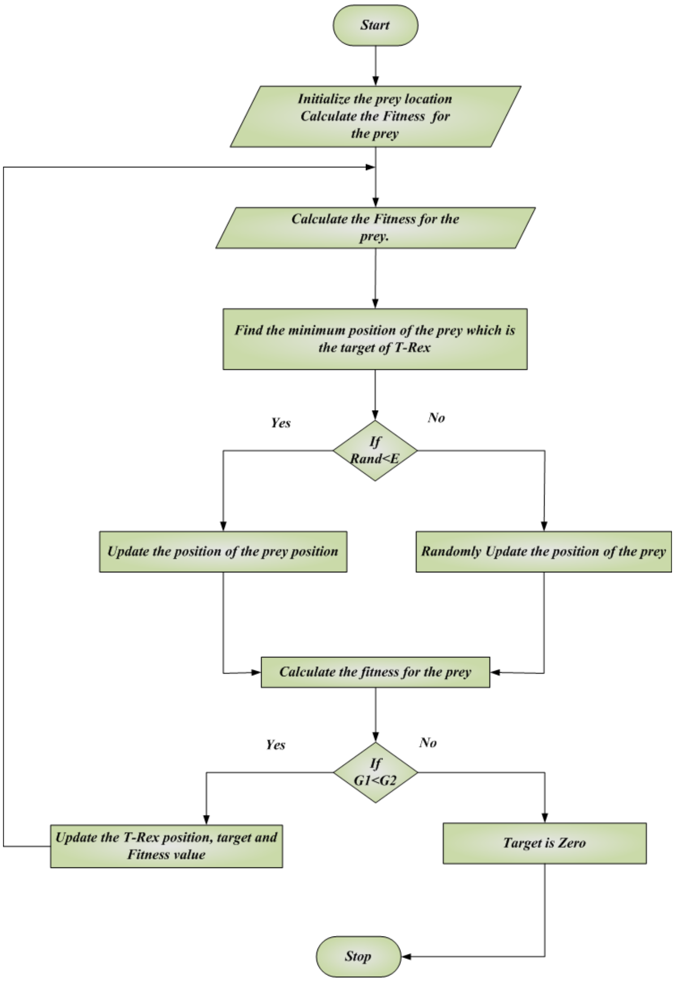

Figure 2: Flowchart of TOA

Step 6: Termination

In this stage, the weight parameter ($G_c \; and \; E^{(u)}$) of Sparse Spectra Graph Convolutional Neural Network are optimized with the help of TOA, iteratively do again the step 3 until the halting is $Y = Y + 1$ met. Then finally proposed SS-CSWBB-RBAGCN predicted deflection behavior of the bridge structure with higher accuracy.

IV. RESULT AND DISCUSSION

This section discusses the proposed method's results. The proposed SS-CSWBB-RBAGCN method is then simulated in Python and compiled utilizing Jupiter notebook and executed in Mac Book Pro along Intel core i7 processor of 2.7 GHz, 8GB of RAM speed. The obtained outcome of the proposed SS-CSWBB-RBAGCN approach is analysed with existing systems like DCCBGB-CSW-BPNN, SCP-SB-XGB and AI-SSSB-CFBNN respectively.

A. Performance Measures

Selecting the best classifier requires taking this critical step. Performance metrics like as accuracy, recall, APE, precision, MSE, MAE, and determination coefficient are evaluated in order to evaluate performance. To scale the performance metrics, the performance metric is deemed. To scale the performance metric, the True Positive (TP), False Positive (FP) ,True Negative (TN), and False Negative (FN) samples are needed.

1) Accuracy

Accuracy is the capacity to measure an exact value. A metric called accuracy can be used to characterize the model's performance in all classes. It is quantified by the following equation (17)

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)} \tag{17}$$

2) Precision

Precision, or whether the model generates positive predictions, is one indicator of a machine learning model's efficacy. The following stated equation (18) is used to measure it.

$$\Pr ecision = \frac{TP}{(TP + FP)} \tag{18}$$

3) Recall

A statistic called recall is used to determine how accurate a forecast was based on the total number of correct positive forecasts. Equation (19), which measures it, is used.,

$$\text{Recall} = \frac{TP}{TP + FN} \tag{19}$$

4) Absolute Percentage Error (APE)

The absolute percentage error serves as a robust performance measure for evaluating the accuracy of deflection predictions in bridge construction models. Its use allows practitioners to gauge the reliability of predictive models, identify areas for improvement, and make informed decisions to optimize construction processes and ensure structural integrity. found in equation (20)

$$APE = \left| \frac{t_i - o_i}{t_i} \right| \times 100\% \tag{20}$$

5) Mean Squared Error (MSE)

An industry standard for calculating the average of squares of mistakes or deviations between predicted and actual values in a dataset is the mean squared error. The following is the formula used to determine MSE:

$$MSE = \left(\frac{1}{n} \right) * \sum \left(x_i - \hat{x}_i \right)^2 \tag{21}$$

6) Mean Absolute Error (MAE)

The regression model's performance is assessed using a statistic called Mean Absolute Error, or MAE. It calculates the mean of the magnitude of the errors between the real and anticipated values.

$$MAE = \frac{\sum_{i=1}^{N} \left| Y_i - \hat{Y}_i \right|}{N} \tag{22}$$

7) Determination Coefficient

In a regression model, the Determination Coefficient (R^2) shows the percentage of the dependent variable's variation that can be predicted by the independent variables. To calculate the Determination Coefficient (R^2), use the formula below:

$$R^2 = 1 - \left(SSres \middle/ SStot \right) \tag{23}$$

Where $SSres$ represent the residuals' sum of squares and $SStot$ represent the entire sum of squares.

B. Performance Analysis

The simulation outcome of the proposed SS-CSWBB-RBAGCN method are shown in Figure 3 to 9. Then, the proposed SS-CSWBB-RBAGCN method is likened with existingDCCBGB-CSW-BPNN, SCP-SB-XGB and AI-SSSB-CFBNNmethods respectively.

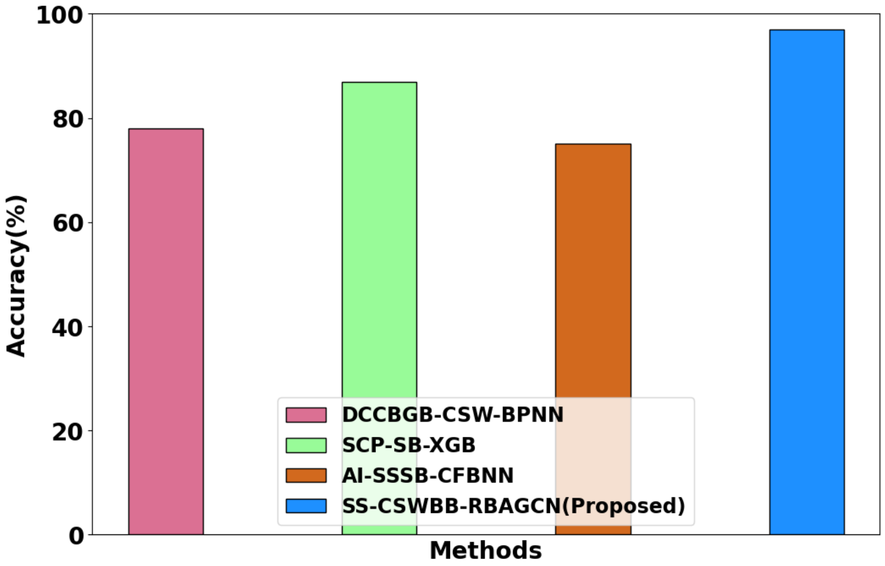

Figure 3: Performance analyses of Accuracy

Figure 3 displays performance analyses of accuracy. The SS-CSWBB-RBAGCN model is a highly accurate prediction model that can be visually represented through graphs that compare the predicted values by the model. This kind of model is necessary for making reliable decisions in bridge construction and maintenance, ensuring structural safety, and optimizing design parameters. The proposed SS-CSWBB-RBAGCN technique reaches in the range of 29.36%, 23.27% and 26.42% higher accuracy, compared with existing techniques such as DCCBGB-CSW-BPNN, SCP-SB-XGB and AI-SSSB-CFBNN respectively.

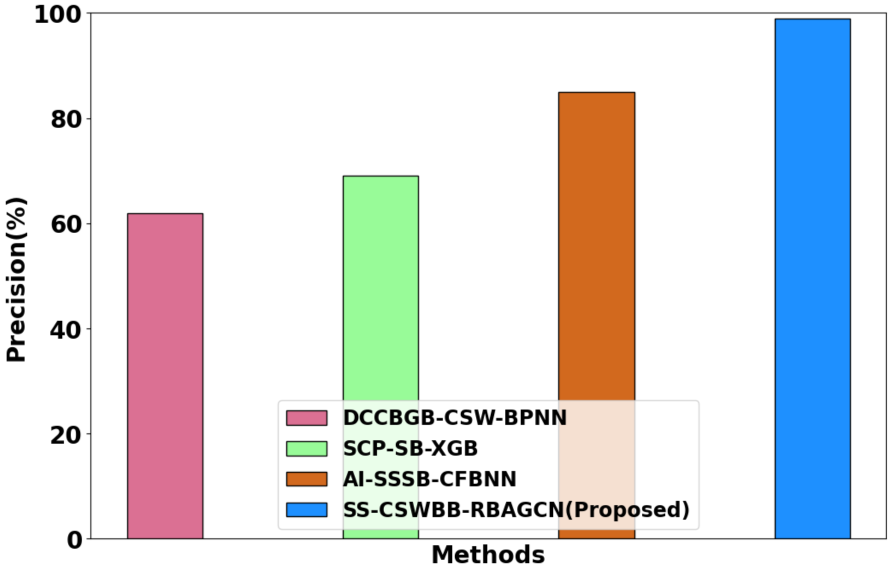

Figure 4: Performance analyses of Precision

Figure 4 displays performance analyses of Precision. The ability of the deflection prediction model for CSWs covered in this research to precisely predict deflection values that closely match the actual deflection values observed in the real-world scenario is referred to as precision. A precise model would have a higher percentage of right predictions than wrong ones. The proposed SS-CSWBB-RBAGCN technique reaches in the range of 18.36%, 16.42% and 28.27% higher precision, compared with existing techniques such as DCCBGB-CSW-BPNN, SCP-SB-XGB and AI-SSSB-CFBNN respectively.

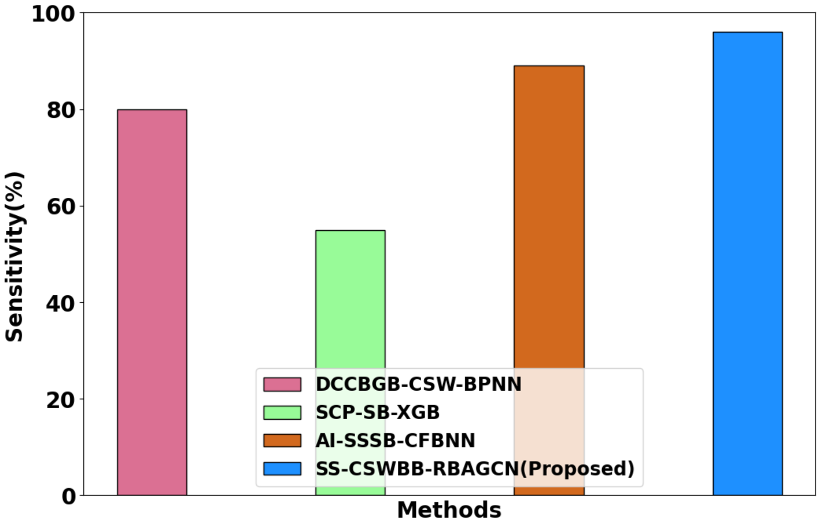

Figure 5: Performance analyses of sensitivity

Figure 5 displays performance analyses of Sensitivity. Sensitivity analysis is a method for determining and measuring how changes in input parameters or other factors affect a model or system's response or output.. The research covers a deflection prediction framework for CSWs, and sensitivity analysis is a fundamental part of that framework. It helps evaluate how various parameters affect the deflection behavior of the bridge structure. The proposed SS-CSWBB-RBAGCN technique reaches in the range of 17.27%, 17.42% and 25.36%higher sensitivity, compared with existing techniques such as DCCBGB-CSW-BPNN, SCP-SB-XGB and AI-SSSB-CFBNN respectively.

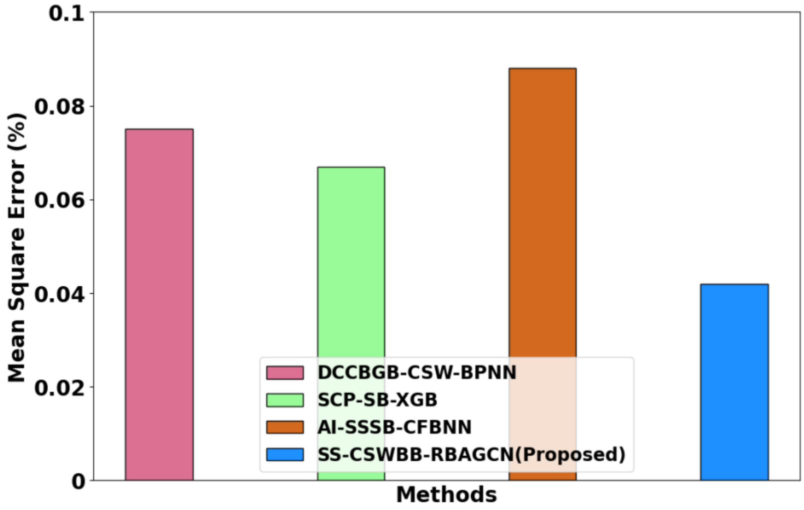

Figure 6: Performance analyses of Mean square Error (MSE)

Figure 6 displays performance analyses of Mean square Error. MSE would be used to evaluate the SS-CSWBB-RBAGCN model's prediction performance to that of the other methods in the deflection prediction framework for CSWs. In order to guarantee the structural integrity and safety of the bridge during building and operation, a lower MSE would suggest that the model is producing more accurate predictions of deflection. The proposed SS-CSWBB-RBAGCN technique reaches in the range of 16.36%, 18.42% and 29.27% lower MSE, compared with existing techniques such as DCCBGB-CSW-BPNN, SCP-SB-XGB and AI-SSSB-CFBNN respectively.

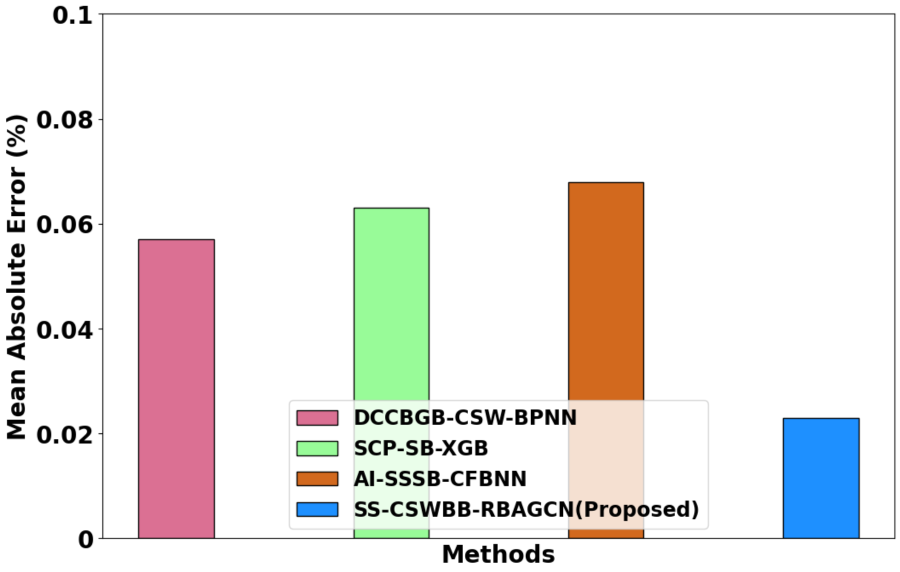

Figure 7: Performance analyses of Mean Absolute Error (MAE)

Figure 7 displays performance analyses of Mean Absolute Error. To evaluate the SS-CSWBB-RBAGCN model's prediction performance against the current techniques for deflection values, MAE would be employed in the framework for deflection prediction for CSWs. In order to guarantee the structural integrity and safety of the bridge throughout construction and operation, a lower MAE would suggest that the model is producing more accurate forecasts of deflection. The proposed SS-CSWBB-RBAGCN technique reaches in the range of 19.36%, 26.42% and 23.27% lower MAE, compared with existing techniques such as DCCBGB-CSW-BPNN, SCP-SB-XGB and AI-SSSB-CFBNN respectively.

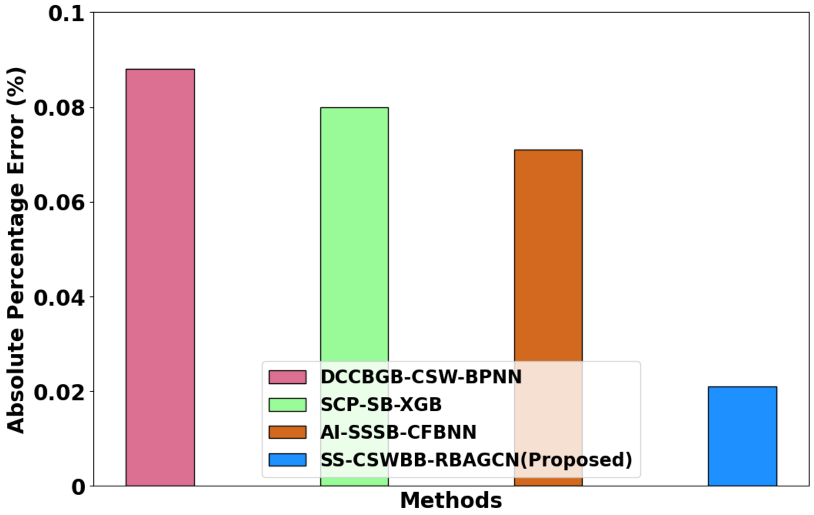

Figure 8: Performance analyses of Absolute Percentage Error

Figure 8 displays performance analyses of Absolute Percentage Error. The average percentage difference between the expected deflection values from the SS-CSWBB-RBAGCN neural network model and the actual deflection values obtained would be evaluated using the Absolute Percentage Error. For the bridge structure to be reliable and safe during the design and construction stages, a lower APE suggests that the model is producing predictions with reduced percentage errors. The proposed SS-CSWBB-RBAGCN technique reaches in the range of 18.46%, 20.38% and 15.45%lower Absolute Percentage Error, compared with existing techniques such as DCCBGB-CSW-BPNN, SCP-SB-XGB and AI-SSSB-CFBNN correspondingly.

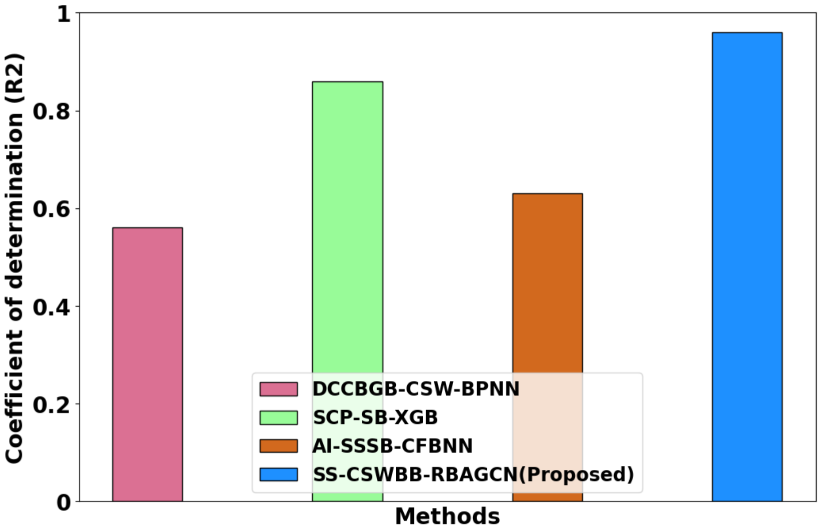

Figure 9: Performance analyses of Determination Coefficient

Figure 9 illustrates performance analyses of Determination Coefficient. The determination coefficient value would be used to evaluate how effectively the SS-CSWBB-RBAGCN model explains the variance in the deflection values compared to the actual deflection values obtained in the deflection prediction framework for CSWs. For precise structural analysis and design, a model must be able to forecast deflection and capture the variability in the deflection data, which is shown by a higher determination coefficient value. The proposed SS-CSWBB-RBAGCN technique reaches in the range of 18.26%, 28.41% and 29.41% higher Determination Coefficient compared with existing techniques such as DCCBGB-CSW-BPNN, SCP-SB-XGB and AI-SSSB-CFBNN respectively.

C. Discussion

The research described in this paper uses a SS-CSWBB-RBAGCN model to establish a prediction approach for deflection in CSWs. The research demonstrates how the SS-CSWBB-RBAGCN model can be effectively used to forecast deflection values, which are essential for guaranteeing structural integrity while building a bridge. The model's capacity to capture the variability in deflection data is highlighted by the evaluation criteria, which include MAE and Determination Coefficient. The RBAGCN neural network as a powerful computational tool for deflection prediction in complex bridge construction processes. The integration of evolutionary computation with back-propagation techniques enhances the neural network's performance, making it a valuable asset for optimizing deflection control in CSWs-PC bridge construction. By providing a dependable and effective prediction framework that can support structural analysis and deflection control, the research advances the field of bridge engineering and eventually improves the safety and dependability of composite box-girder bridges.

V. CONCLUSION

In this section, Structural Strength of Corrugated Steel Web Box Beam Based on Finite Element Analysis (SS-CSWBB-RBAGCN)is successfully implemented. The proposed SS-CSWBB-RBAGCN approach is implemented in Python. The performance of the proposed SS-CSWBB-RBAGCN approach contains 29.36%, 23.27% and 26.42% higher accuracy, 18.46%, 20.38% and 15.45% lower Absolute Percentage Error and 18.26%, 28.41% and 29.41% higher Determination Coefficient when analysed to the existing methods like DCCBGB-CSW-BPNN, SCP-SB-XGB and AI-SSSB-CFBNN methods respectively. To increase prediction efficiency and accuracy, more research may look into optimizing model parameters and training procedures. Future research endeavours to improve the predictive power of the suggested model and bolster its usefulness in stress and deflection management for intricate engineering structures such as composite box-girder bridges using corrugated steel webs.

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