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Mechanical Property Prediction Model Based on Concrete Microstructure and Its Application in Seismic Reinforcement

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Abstract: - Seismic reinforcement is a critical aspect of ensuring structural integrity during earthquakes. Concrete, a ubiquitous construction material, plays a vital role in seismic resistance. In this manuscript proposes a Mechanical Property Prediction Model Based on Concrete Microstructure and Its Application in Seismic Reinforcement (MPPB-CAMSR- RICCNN). Initially, the data is collected from the “Concrete Data” information set. Then, the collected information is fed to Get Ready for processing segment. In to Get Ready for processing stage, then, the input data are pre-processed using Multivariate Fast Iterative Filtering (MFIF) is used to clean the data. Then pre-processed output is given to RICCNNthat predicts the mechanical properties of high-performance fiber-reinforced cementations composites (HPFRCC). The weight parameters of RICCNN are optimized using Banyan Tree Growth Optimization (BTGO). The planned MPPB-CAMSR- RICCNN method is implemented and the presentation metrics like Correctness, exactness, compassion, specificity, F1-score, and computational time are appraised. The presentation of suggested technique was executed in the Python structure. The performance of the suggested MPPB-CAMSR- RICCNN approach attains22.5%, 21.5% and 26% higher accuracy, 23.06%, 25.33% and 20.98% higher Precision and 22.12%, 20.33% and 23.98% higher compassion compared with present methods like Predicting Mechanical Properties of HPFRCC by Integrating Micromechanics and Machine Learning (PMHPR-ML), A Predictive Mimicker of Fracture Behavior in Fiber Reinforced Concrete Using Machine Learning (PMFRC-ANN), and Hybrid machine learning-based prediction model for the bond strength of corroded Cr alloy-reinforced coral aggregate concrete (PBSCAC-SVR).By comparing other three existing methods, the proposed MPPB-CAMSR- RICCNN method gives high accuracy models respectively.

Keywords: Concret, Rotation-Invariant Coordinate Convolutional Neural Network, Multivariate Fast Iterative Filter, Banyan Tree Growth Optimization, mechanical properties.

I. INTRODUCTION

Concrete, a fundamental material in construction, has a vital part throughout structural integrity in buildings also infrastructure [1-3]. Its mechanical properties, which determine its strength and durability, are directly influenced by its microstructure [4, 5]. Predicting and comprehending these characteristics are crucial to guaranteeing the durability and safety of concrete constructions, especially in seismic regions where the material must withstand dynamic and unpredictable forces [6, 7]. The ability to accurately model the mechanical possessions of real based on its microstructure may significantly enhance a design then reinforcement of buildings, contributing to better resilience against earthquakes [8]. However, forecasting the mechanical possessions of real based on its microstructure presents several challenges [9]. Traditional models often fail to capture the complex interactions within the microstructure, leading to inaccuracies in property estimation [10, 11]. Additionally, the heterogeneity of building materials, impacted by elements including the distribution of aggregates, cements composition, and curing conditions, adds to the complexity [12]. These limitations can result in suboptimal design and inadequate reinforcement strategies, potentially compromising the structural integrity during seismic events [13]. To address these challenges, advanced modelling techniques incorporating machine learning and high-resolution imaging of concrete microstructure have been developed. By leveraging these technologies, more accurate and comprehensive models can be created, capturing the intricate details of the concrete's internal composition [14]. These models can provide better predictions of mechanical properties, enabling more effective seismic reinforcement strategies. Integrating these advancements into engineering practices can enhance the safety and resilience of concrete structures, particularly in earthquake-prone areas.

Several works were have presented previously in literatures were depending on Mechanical Property Prediction Model Based on Concrete using deep learning. Few of them were mentioned here. P Guo et al. [15] have created a machine education technique for the successful and effective growth of HPFRCC. With the creative

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integration of micromechanics, this research specifically creates machine learning examples to forecast the mechanical possessions of HPFRCC. The goal is to improve the generalization performance and prediction accuracy by inspiring and enhancing the information set using principal component analysis (PCA), data cleaning, and K-fold cross-authentication.

This work not only forecasts the compressive and tensile strengths but also, for the first time, the ductility of HPFRCC by taking into account an entire of 14 distinct mix design factors. A variety of machine learning techniques are examined and contrasted, like support vector regression (SVR), extreme gradient boosting tree (XGBoost), classification and regression tree (CART), and artificial neural network (ANN).

A machine knowledge model that can prediction any kind of fiber-reinforced concrete subclass's fracture behavior, especially that of strain-hardening designed for cementations materials, has been created by Khokhar et al. [16]. This study assesses fifteen input parameters, such as the fiber characteristics and the components of the mixed design. These consist of the dangerous gradient boosting tree, the classification and reversion tree, the provision vector machine, the Gaussian procedure of reversion, and artificial neural networks. The results show that the XGBoost model is the best mimicker for predicting the features of fiber-reinforced concrete, since it has the lowest error. It is expected to significantly enhance the recipe design of efficient formulations for fiber-armour-plated concrete.

Founded on experimental and hybrid machine knowledge, Sun et al. [17] have examined the bond slip conduct of recently produced Cr alloy steel bars and CAC. A number of different variables were looked at, including the corrosion ratio, diameter, CAC strength, anchoring length, and relative protective layer thickness (a, b, c, d, e). The findings demonstrated a negative correlation among bond strength and diameter and anchoring length and a positive correlation with CAC intensity and relative protection layer thickness. As the corrosion ratio grew, the bond strength first increased and then decreased, reaching a critical threshold of 1%. There were four steps on the Cr–CAC bond-slip curve: microslip, slip, decreasing, and residual. Furthermore, a range of performance assessment measures were employed to assess the empirical, BP, provision vector machine regression (SVR), and particle swarm optimization backpropagation (PSO-BP) models.

Kavya et al. [18] Using information from the literature, an ANN model has been created to forecast the fortes of real with glass and basalt fibers at a 28-day real age. The characteristics taken into consideration for the ANN inputs included the ratios of fine to coarse aggregate to cement, water to cement, fly ash to cement, super plasticizer to cement, fiber content, its diameter, density, elastic modulus, length, and the concrete strengths as objectives. Saradar et al. [19] have investigated the mechanical properties of lightweight structural concrete with expanded clay aggregate and different proportions of basalt fibers (0–0.5%). Therefore, in order to replace some of the cement weight in lightweight concrete mixes, pozzolanic elements such as fly ash and silica fume were utilized to change some of the concrete's qualities. Twenty-one mix designs in all were created, and at various ages of seven, twenty-eight, and ninety days, their fresh and hardened characteristics were evaluated. According to the results, basalt fibers decreased compressive strength and slump by 13% and 37%, respectively. Additionally, it was discovered that every combination had a "good" degree of water absorption quality, qualifying it as "structural concrete." To forecast the flexural strength and compressive strength of cement mortar coveringnano- and micro-silica (NS and MS),

Jueyendah et al. [20] developed a method. They looked into the possibility of using the support vector machine (SVM) approach using four different kernels: radial basis function (RBF), polynomial, linear, and sigmoid. The dataset used to determine the input parameters included 32 mixtures, 32 flexural specimens, 480 compressive specimens, and 7 mix design variables, including the ratios of water to cement (W/C), sand to cement (S/C), nano- and micro-silica to cement (NS/C), age, and porosity of the specimens. Furthermore, the radial basis function (RBF) network, general regression neural network (GRNN), and multilayer perceptron (MLP) neural networks were used to estimate the strength of the cement mortar.

The relationship amongmeso- and macro-properties is recognized by Wang et al.'s [21] investigation into the relationship between strength and pore characteristics of basalt fiber-reinforced concrete (BFRC) with varying fiber concentrations. The study examines the compressive, flexural, and splitting tensile strengths of BFRC with varying fiber concentrations at eight different admixture levels. T2 spectra of BFRC with different fiber contents were acquired using the nuclear magnetic resonance (NMR) method, yielding curves representing the pore distribution. Furthermore, taking into account the characteristics of various pore size proportions, the article explores the effect of pore construction on the unique mechanical possessions of BFRC by grey correlation analysis. This work constructs GM(1,3) prediction models for three strengths, respectively, using the ideal pore structure limits determined from GCA to anticipate distinct strengths. A considerable link between strength and pore modifications is indicated by the thorough correlation between BFRC strength ranges and pore parameters. Based on the most important pore construction characteristics found in the GCA, a formula for a BFRC strength forecast model was created. This calculation method demonstrates a high degree of accuracy in forecasting the strength of BFRC, providing a quantitative link between the mesoscopic and macroscopic levels that efficiently guides the manufacturing and use of BFRC.

Several works have presented various machine knowledge approaches for forecasting mechanical possessions of concrete, yet each method exhibits certain drawbacks. Common issues include the complexity and computational expense of certain models like artificial neural networks (ANN) and extreme incline boosting trees (XGBoost), which can be challenging to implement and require significant computational resources. Some studies may face limitations in generalizability due to the specificity of their datasets, such as those focusing on particular types of fiber-reinforced concrete or specific environmental conditions, which might not be representative of broader applications. Models like SVR and classification and regression trees (CART) may struggle with scalability and handling high-dimensional data, potentially leading to overfitting or underfitting issues. Additionally, the reliance on extensive experimental datasets to train these models can be a significant drawback, as gathering and preparing large amounts of data is often resource-intensive. Furthermore, the interpretability of complex models can be limited, making it difficult to derive clear, actionable insights from the predictions, which is a crucial aspect for practical applications in the building industry.

To overcome drawbacks in predicting mechanical possessions of concrete using deep learning, integrating advanced techniques such as transfer learning and hybrid models can be effective. Transfer learning allows the use of pre-trained models on similar tasks, significantly reducing the need for extensive datasets and computational resources. Hybrid models that combine deep learning with traditional machine learning techniques can enhance prediction accuracy and interpretability. Additionally, employing automated machine learning (AutoML) can streamline data preprocessing, feature selection, and model tuning, thus simplifying implementation. Utilizing cloud-based computing resources can mitigate computational expense, making high-performance models more accessible. To address generalizability, diverse and comprehensive datasets should be curated, encompassing a wide range of concrete types and environmental conditions. Improving model interpretability can be achieved through techniques like model-agnostic methods and attention mechanisms, which help elucidate the decision-making process of complex models, thus making the insights more actionable for practical applications.

The main charities of this investigation work are potted below

- In this research, Mechanical Property Prediction Model Based on Concrete Microstructure and Its Application in Seismic Reinforcement (MPPB-CAMSR- RICCNN) is proposed.
- The "Concrete Data" dataset is where the data is first gathered.
- RICCNN method used to predicts the mechanical properties of HPFRCC
- BTGO is used to improve the weight strictures of RICCNN.
- The suggested technique is executed in the Python platform.

Rest of these manuscripts is prearranged as follows: Part 2 describes the proposed methodology, Part 3proves the result with discussion and Part 4concludes this manuscript

II. PROPOSED METHODOLOGY

In this proposed methodology, Mechanical Property Prediction Model Based on Concrete Microstructure and Its Application in Seismic Reinforcement (MPPB-CAMSR- RICCNN)is proposed. This process consists of four steps: Dataset, Pre-processing using Multivariate Fast Iterative Filtering (MFIF).The RICCNN method used to forecast the mechanical possessions of HPFRCCBTGO. Block Diagram of offered MPPB-CAMSR- RICCNN method is signified by Figure 1.

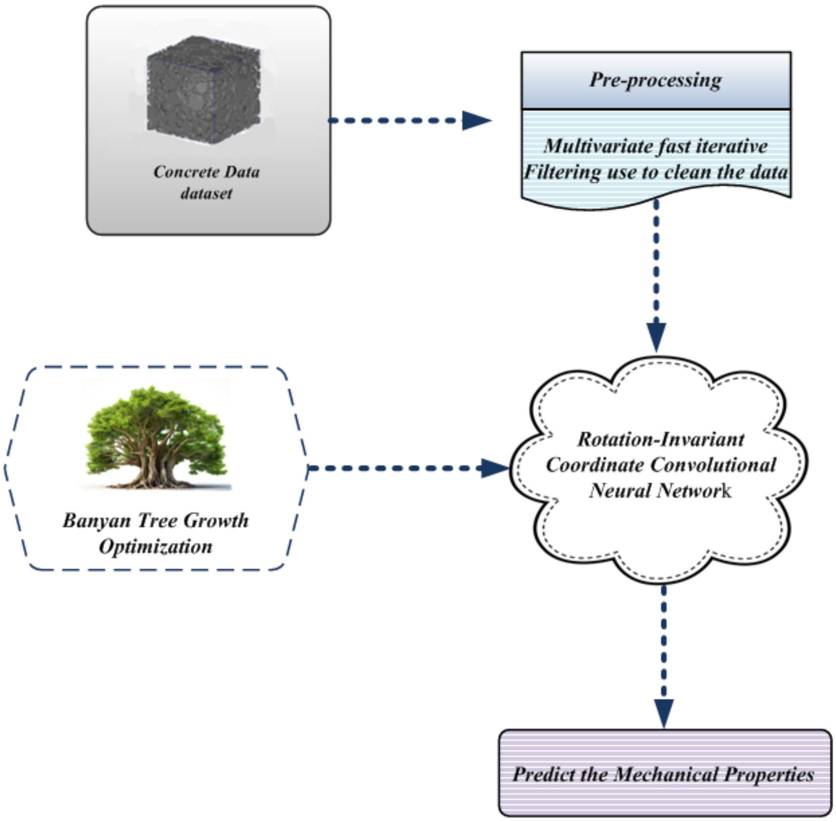

Fig 1: Block Diagram of proposed MPPB-CAMSR- RICCNN method

A. Data Acquisition

Initially the input information is composed from the 'Concrete Data' information set [22]. The Concrete Dataset offers a comprehensive examination of concrete mixtures and their corresponding strength attributes, providing valued visions into the material possessions and presentation of concrete structures. This dataset encompasses various factors influencing concrete strength, such as the composition of ingredients, curing conditions, and age at testing. It includes 1,030 instances and 9 attributes: Cement (kg in a m^3 mixture), Blast Furnace Slag (kg in a m^3 mixture), Fly Ash (kg in a m^3 mixture), Water (kg in a m^3 mixture), Super plasticizer (kg in a m^3 mixture), Coarse Aggregate (kg in a m^3 mixture), Fine Aggregate (kg in a m^3 mixture), Age (days), and Compressive Strength (MPa). The first eight attributes represent the features detailing the various components and their quantities used in the concrete mixture, while the ninth attribute, Compressive Strength, is the target variable indicating the strength of the concrete after a specified number of days. This dataset is commonly applied in machine learning and statistical modelling tasks, especially regression analysis, to explore the relationship between concrete composition and its resultant strength.

B. Pre-Processing using Multivariate Fast Iterative Filtering (MFIF)

In this section, we discuss the pre-processing of the input data using Multivariate Fast Iterative Filtering (MFIF) [23]. The objective of MFIF is to clean the data. Since fast iterative filtering techniques are designed to process and filter data quickly, they are frequently suitable for applications in actual time or nearly real-time. Multivariate approaches can handle multiple variables or qualities simultaneously, which is beneficial when working with complex datasets that require an understanding of the correlations between various variables. In general, the goal of filtering techniques is to enhance the quality of the data. MFIF procedure is to first calculate in certain way a single sieve length L, which signifies half provision length of the filter function W, and then usage it to excerpt the first Intrinsic Mode Functions (IMF) from each of the n channels separately via FIF.

$$\theta(r) = \arccos\left(\frac{u(r)}{u(r)} \cdot \frac{u(r-1)}{u(r-1)}\right) \tag{1}$$

Here, $\theta(r)$ is denotes filter length, $u(r)$ is denotes sequence of column vectors and $u(r-1)$ it represent the initial velocity. Calculating the double average distance among subsequent extreme and $\theta(r)$ allows approximating the regular scale of the maximum incidence rotations entrenched in the given data and stopping criterion (RD) is defined as the given equation (2),

$$RD = \max_{j=1,\ m} \left\| v_i^{(l+1)} - v_i^{(l)} \right\|_2 < \delta \quad \forall l \geq Mo \tag{2}$$

Where, RD is denotes a stopping criterion, v_i is denotes a Fourier transform, $v^{(l)}$ is denotes a value of the IMF and l denotes an inner loop. The Discrete Fourier transform is circular, meaning its basis is polynomials on the roots of unity which are invariant under cyclic shifts. Given $l = 0$, diagonal matrix becomes diagonal, when the vectors are orthonormal, such that their inner product is zero. This has given in the equation (3)

$$JNG = \left[jEGS\left((J-E)^{Po} EGS\left(v_j^S\right)\right)^S \right]_{j=1,\dots,p} \tag{3}$$

Where $jEGS$ is a slanting data covering as entries the eigen values of the separate difficulty data EGS is denotes the associated with the filter and also construct the discrete convolution operator related with w. A set of linearly independent vectors are defined as the given equation (4),

$$v_p = \frac{1}{\sqrt{n}} \left[1, f^{-2\pi i p \frac{1}{n}}, \dots, f^{-2\pi i p \frac{n-1}{n}}, \dots \right] \tag{4}$$

Where, p denotes a group of elements, v_p denotes the unitary matrix, π represent the eigenvalues, f denotes the number of the elements. The diagonal matrix eigenvalues are defined as the following equation (5),

$$\lambda_q = \sum_{r=0}^{n-1} c_{1p} f^{-2\pi i p \frac{p}{m}} \tag{5}$$

Where, λ_q is denotes distinct eigenvalues, n denotes the filter, p denotes positive intervals, and m denotes a number of positive integers. Finally the MFIF has to resize pixels to confirm the desired input clean the data. Then, the pre-processed data is given to prediction section by using neural network.

C. Predict the Mechanical Properties of HPFRCC using Rotation-Invariant Coordinate Convolutional Neural Network (RICCNN)

In this section, RICCNN [24] is discussed for forecast the Mechanical Possessions of HPFRCC. The RICCNN offers the advantage of processing input data regardless of its orientation, thus enabling accurate analysis of structural materials like HPFRCC, where fiber orientation may vary, resulting in more robust and reliable predictions of mechanical properties. Furthermore, RICCNN can handle irregular and complex micro structural features inherent in HPFRCC, allowing for comprehensive analysis and prediction of mechanical behavior compared to traditional methods, and efficiently utilizes large datasets to extract nuanced patterns and correlations, contributing to improved accuracy in predicting mechanical properties.By utilizing the RICCNN in forecasting the mechanical possessions of HPFRCC, the model's generalization across different orientations is enhanced, rendering it more practical and accurate for real-world applications. This advancement also contributes to improved accuracy in structural period calculations, as described by equation (6),

$$\Phi_{RIC-C}(Y_0, X(F)) = \sum_{Q \in T_{X_0}} M(L) \cdot X(Y_0 + Q)$$

(6)

Where, Φ_{RIC-C} denotes the function of Y_0; Y_0 denotes the fixed input function; $X(F)$ denotes a function of L; $M(L)$ denotes the convolutional kernel point; and Q denotes a sample point. The convolutional procedure involves sweeping a filter over the input data to capture structural characteristics crucial for predicting the mechanical properties of concrete. Convolutional layers analyze spatial patterns inherent in the material's microstructure, enabling accurate estimation of concrete behaviour. Convolutional layers analyze spatial patterns inherent in the material's microstructure, enabling accurate estimation of concrete behaviour. This hierarchical learning facilitates precise prediction of structural behavior, enhancing the model's ability to forecast the mechanical possessions of concrete with accuracy. The convolutional operation is defined as equation (7),

$$Q'_m = R_\theta Q_m \tag{7}$$

Where, Q'_m denotes the prime derivative of Q_m ; R_θ denotes a coefficient angle that scales the rate of change of Q_m . A deep learning framework that can analyse spatial data that is sensitive to rotational fluctuations is called a RICCNN. This equation serves as a foundation for analyzing the mechanical properties of concrete using the RICNN framework, which effectively handles spatial data sensitive to rotational fluctuations, offering accurate estimations of fundamental periods in masonry infill reinforced concrete frame constructions. The reinforced concrete frame structure defined as equation (8),

$$\Phi_{RIC-C}(Y_0, X(F)) = \sum_{P \in S} M(L) \cdot L(Y_0 + K + \Delta K) \tag{8}$$

Where, Φ_{RIC-C} denotes the function Y_0 ; Y_0 denotes the fixed input function; $X(F)$ denotes a function of Z ; $M(L)$ denotes the convolutional kernel point and ΔK denotes the difference of variable K . This equation illustrates the process of enhancing the resilience and generalization of structural analysis for forecasting the mechanical possessions of concrete. Utilizing specific deep learning algorithms, RICCNN, similar to RICCNN, accurately forecasts the basic period of masonry infill reinforced concrete frame constructions. Similarly, RICCNN can be defined using the following equation (9),

$$\Phi_{RIC-C}(Y_0, X(F)) = \sum_{P \in S} M(L) \cdot L(Y_0 + K + (Q - K)) \tag{9}$$

Where, Φ_{RIC-C} denotes the function Y_0 ; Y_0 denotes the fixed input function; $X(F)$ denotes a function of Z ; $M(L)$ denotes the convolutional kernel point and $Q and K$ denotes a sample point. Finally, RICCNN have predicted the Mechanical Properties of HPFRCC. Then the BTGO is employed to optimize the RICCNN. Here BTGO is employed for tuning the weight and bias parameter of RICCNN.

D. Optimization Using Banyan Tree Growth Optimization (BTGO)

This section describes the proposed BTGO [25] is discussed. The RICCNN weight parameter R_θ *and* K is optimized by BTGO. BTGO is an innovative procedure enthused by the natural development patterns of banyan trees. One significant advantage of BTGO is its efficient exploration of the search space, akin to how banyan trees extend their roots and branches extensively, thereby improving the likelihood of discovering global optima. Additionally, BTGO is highly adaptable and flexible, capable of dynamically adjusting its growth patterns to suit different optimization problems, making it a versatile choice for a wide range of applications. Moreover, BTGO demonstrates robust performance in handling complex, multimodal optimization problems, effectively avoiding premature convergence and exploring multiple potential solutions concurrently. This robustness ensures reliable and accurate results in diverse and challenging optimization scenarios. BTGO promotes trust by upholding honesty, which facilitates long-term development and innovation in audio-related fields. Banyan Tree Growth Optimization

Step 1: Initialization

Initialize the input parameters, here the input parameter are the weight parameter search agents is shown in equation (10)

$$y_j = \begin{bmatrix} y_{j1} & \cdots & y_{jN} \\ \vdots & \ddots & \vdots \\ y_{jk} & \cdots & y_{jN} \end{bmatrix} 1 \le j \le O, 1 \le k \le N \tag{10}$$

Where, shoulder an initial branch population y with O individuals. Each separate denotes a set of incessant solutions with N sizes, and the j separate.

Step 2: Random Generation

After initialization, weight limits are formed arbitrarily generated. The values of best suitability are selected contingent clear hyper limit situation.

Step 3: Fitness Function

Fitness purpose creates casual solution from prepared values. It calculated using optimizing parameter. Thus it is shown in equation (11),

$$FitnessFunction = optimizing\,[R_\theta \; and \; K] \tag{11}$$

Where, σ is used to increasing the high accuracy and δ is reducing the Computation time.

Step 4: Generate the initial branches $[\sigma]$

The optimal growth of banyan trees necessitates the careful consideration of environmental characteristics such as sunlight, soil nutrients, and water availability in order to provide the right conditions for root growth and canopy development. By using selective pruning and training techniques, it is possible to reduce overcrowding and encourage healthy branching, which will help to develop a robust and well-structured tree. Furthermore, biodiversity promotion in the surrounding ecosystem may help the tree develop by promoting favourable interactions with other plants and species.

$$y_{jk} = y_{\min,k} + rand \times \sigma\left(y_{\max,k} - y_{\min,k}\right) \tag{12}$$

Where, $rand$ denotes the random number, $y_{\max}$ denotes the maximum values, $x_{\min}$ denotes the minimum values,

Step 5: Multi-trunk operator $[\delta]$

Exploitation is main criteria for any Banyan Tree Growth Optimization, the variable which has a random value between 0 and 1. To maximize development potential, focus on improving the root system's nutrient uptake capability through soil enrichment and water- and nutrient-retention irrigation techniques. Purposeful pruning encourages branching and canopy expansion, which efficiently catches sunlight for photosynthesis and overall health. For vigorous development and tolerance to environmental challenges, use organic fertilizers designed to satisfy its specific nutrient needs.

$$y_j = Q_j^{root} + G \times \left(2 \times rand\left(1, E\right) - 1\right) \times \delta\left(y_j - Q_j^{root}\right) \tag{13}$$

Where, Q_j^{root} denotes the j^{th} aerial root examined by the k^{th} branch, $rand\left(1, E\right)$ is a E dimensional vector of chance amounts and G denotes the growth factor which is generally a constant value.

Step 6: Termination Condition

The weight limit standards σ *and* δ of producer from Dual Temporal Gated Multi-Graph Convolutional Recurrent Network is enhanced with the help of BTGO, will iteratively repeat the step 3 until fulfil the hesitant standards $y_j = y_j + 1$ is met. Then DTGMGCN has managed the Accident detection by assessment with higher accuracy. Flowchart of BTGO for optimizing DTGMGCN parameter is shown in figure 2.

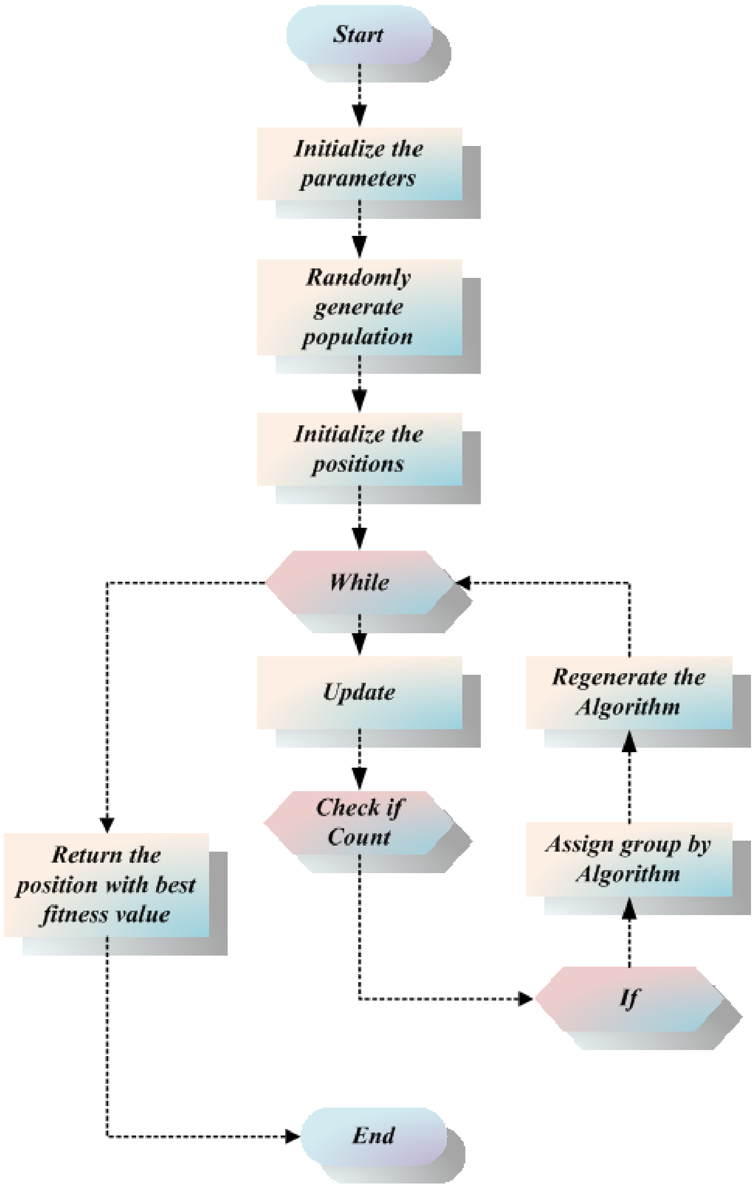

Figure 2: Flowchart of BTGO for optimizing DTGMGCN parameter

III. RESULT WITH DISCUSSION

The outcomes of the suggestedMPPB-CAMSR-RICCNN technique have graded the detected Rheumatoid arthritis automatically. This proposed method is implemented using Python and evaluated by using several presentation analysing metrics like Correctness, Compassion, Exactness, F1- score, Sensitivity and Computational Time are analysed. The results of the proposed MPPB-CAMSR-RICCNN methodology are likened to those current methods likePMHPR-ML [15], PMFRC-ANN [16] and PBSCAC-SVR [17].

A. Performance Metrics

Performance measures include Accuracy, Sensitivity, Precision, F1- score, Compassion and Computational Time. The misperception matrix will be used to scale the performance parameters, it is decided.

- True Positive (TP) : Actual, forecast are both positive
- True Negative (TN) : Actual, forecast are both bad
- False Positive (FP) : Actual is bad, forecast is positive
- False Negative (FN) : Actual is optimistic, forecast is negative

1) Accuracy

The value of correctness is calculated as ratio of the count of samples precisely branded by scheme with whole count of examples, which is computed by equation (14),

$$Accuracy = \frac{(TP+TN)}{(TP+FP+TN+FN)} \tag{14}$$

2) Precision

It assesses a sample's predictive value, which varies depending on the class for which it is calculated; in other words, it determines the sample's prognostic power, which is determined by equation (15).

$$\Pr ecision = \frac{TP}{(TP+FP)} \tag{15}$$

3) Sensitivity

Sensitivity is a statistic that estimates the amount of accurate positive predictions based on the overall amount of positive predictions. It is quantified using the equation that follows. (16),

$$Sensitivity = \frac{TP}{TP+FN} \tag{16}$$

4) Specificity

Specificity is the aptitude of the procedure or model to predict a true bad for each accessible category. In literature, it is frequently mentioned to as the true negative rate. Formally, the following equation (17) can be used to calculate it.

$$Specificity = \frac{TN}{TN+FP} \tag{17}$$

5) F1-score

The F-measure is a measure used to assess the efficiency of a deep learning model. Precision and recall are combined into a single score (F-measure). Thus it’s give this equation (18),

$$F-measure = \frac{\Pr ecision * \mathrm{Re}call * 2}{(\Pr ecision + \mathrm{Re}call)} \tag{18}$$

B. Performance analysis

The imitation outputs of MPPB-CAMSR-RICCNNapproach are portrayed in figure 3 to 8. The suggestedMPPB-CAMSR-RICCNNapproach is compared to existing PMHPR-ML, PMFRC-ANN and PBSCAC-SVRmodels.

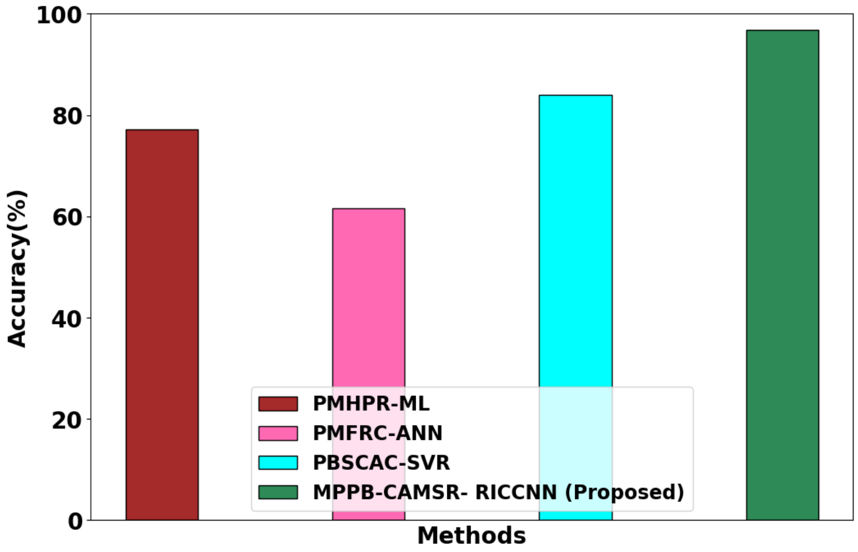

Figure 3: Performance Analysis of Accuracy

The presentation examination of correctness is depicted in figure 3. In the context of planned MPPB-CAMSR-RICCNN method on High-Performance Fiber-Reinforced Cementitious Amalgams (HPFRCC), an accuracy graph shows how well different models including PMHPR-ML, PMFRC-ANN and PBSCAC-SVR perform in predicting mechanical properties. The proposed MPPB-CAMSR-RICCNN method attains 23.32%, 30.12% and 25.05% advanced correctness when likened with current approaches like PMHPR-ML, PMFRC-ANN and PBSCAC-SVR respectively.

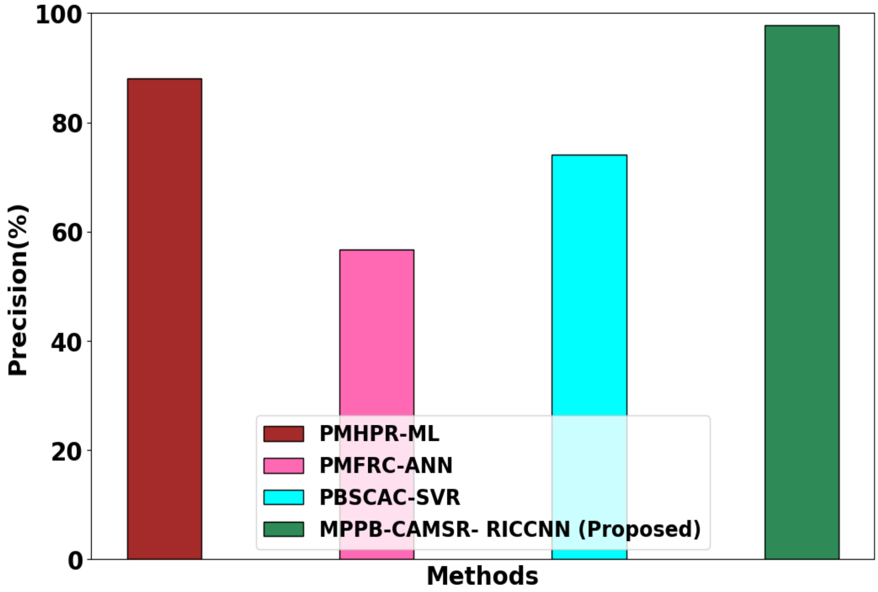

Figure 4: Performance Analysis of Precision

The presentation examination of Precision is represented in figure 4. The precision scores of various models, including PMHPR-ML, PMFRC-ANN and PBSCAC-SVR are displayed in a precision graph in the context of predicting mechanical properties of high-performance fiber-reinforced cementitious composites (HPFRCC) using proposed MPPB-CAMSR-RICCNN method. The proposed MPPB-CAMSR-RICCNN model that is more accurate in predicting qualities like compressive forte, tensile strength, and ductility is highlighted in the graph by comparing the precision scores of these models. The proposed MPPB-CAMSR-RICCNN method attains 22.92%, 23.2% and 21.05% higher Exactness when likened with current methods like PMHPR-ML, PMFRC-ANN and PBSCAC-SVR respectively.

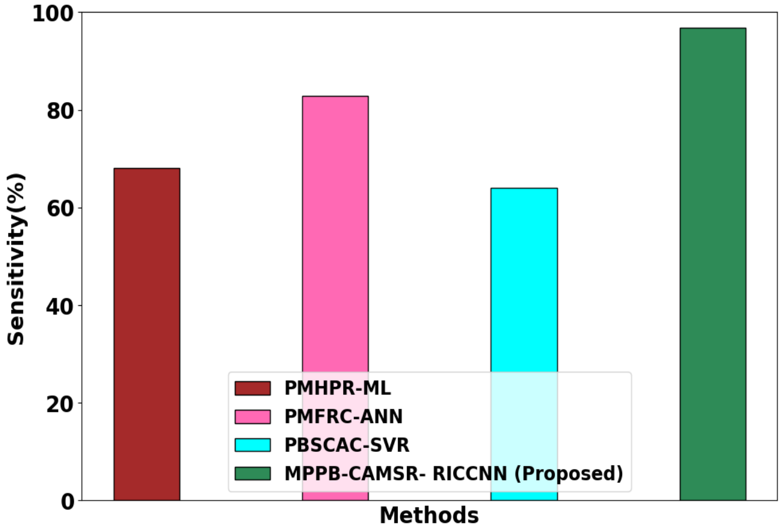

Figure 5: Performance Analysis of Sensitivity

The presentation examination of Sensitivity is portrayed in figure 5. When utilizing proposed MPPB-CAMSR-RICCNN method to forecast the mechanical properties of high-performance fiber-reinforced cementitious composites (HPFRCC), a sensitivity graph shows how various mix design variables alter the expected results. This graph aids in determining which input variables such as aggregate type, fiber content, or the ratio of cement to water have the most effects on mechanical attributes including ductility, tensile strength, and compressive strength. Plotting the prediction proposed MPPB-CAMSR-RICCNN model's sensitivity to each variable allows for the development of HPFRCC formulations and optimization by illuminating the relative importance of each component. The proposed MPPB-CAMSR-RICCNN method attains 24.11%, 23.74% and 26.21% higher Compassion when likened with present methods like PMHPR-ML, PMFRC-ANN and PBSCAC-SVR respectively.

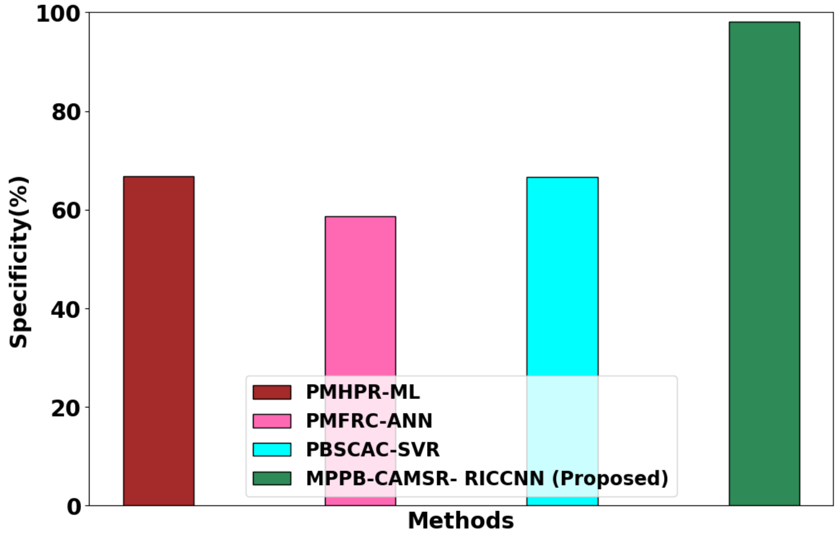

Figure 6: Performance Analysis of Specificity

The presentation examination of Specificity is portrayed in figure 6. When it comes to utilizing proposed MPPB-CAMSR-RICCNN method to forecast HPFRCC, specificity graph shows how well the proposed MPPB-CAMSR-RICCNN method models are able to identify real negatives, or negative cases out of all actual negative instances. This graph illustrates the specificity of PMHPR-ML, PMFRC-ANN and PBSCAC-SVR performance for properties like compressive strength, tensile strength, and ductility. By comparing how well the proposed MPPB-CAMSR-RICCNN model performs in precisely identifying situations in which the material does not exhibit the intended mechanical feature, it provides valuable information on the applicability and trustworthiness of the model for real-world material development applications. The proposed MPPB-CAMSR-RICCNN method attains 29.01%, 25.11% and 21% higher Specificity when compared with present methods like PMHPR-ML, PMFRC-ANN and PBSCAC-SVR respectively.

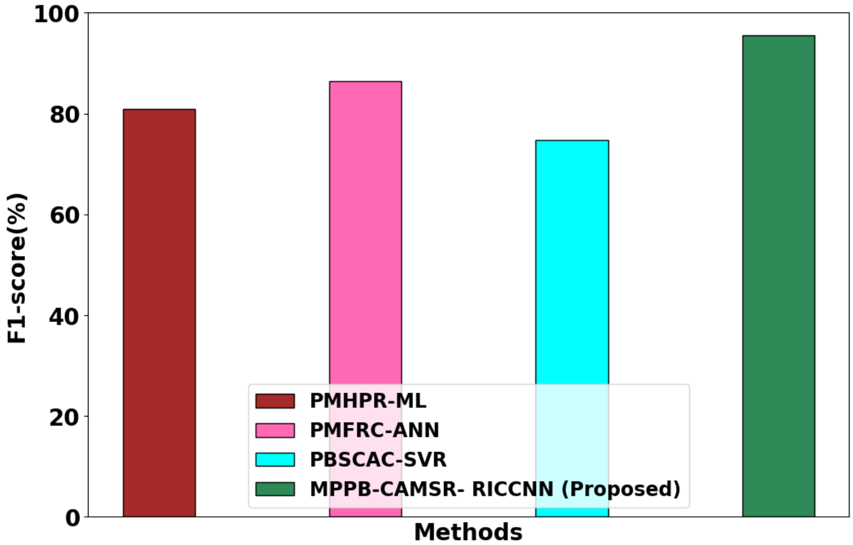

Figure 7: Performance Analysis of F1-Score

The presentation analysis of F1-Score is depicted in figure 7. The balance between precision and recall for each model, such as PMHPR-ML, PMFRC-ANN and PBSCAC-SVR would be displayed in an F1-Score graph for HPFRCC. The Y-axis would display the F1-Score, which is the vocal mean of exactness and memory and indicates how well the proposed MPPB-CAMSR-RICCNN model predicts attributes like ductility and compressive and tensile strengths. The X-axis would display various models. This graph provides insights into the overall presentation and predictability of the planned MPPB-CAMSR-RICCNN model by illustrating which model offers the best trade-off between precision and recall. The proposed MPPB-CAMSR-RICCNN method attains 22.58%, 23.23% and 25.12% higher F1-Score when compared with current methods like PMHPR-ML, PMFRC-ANN and PBSCAC-SVR respectively.

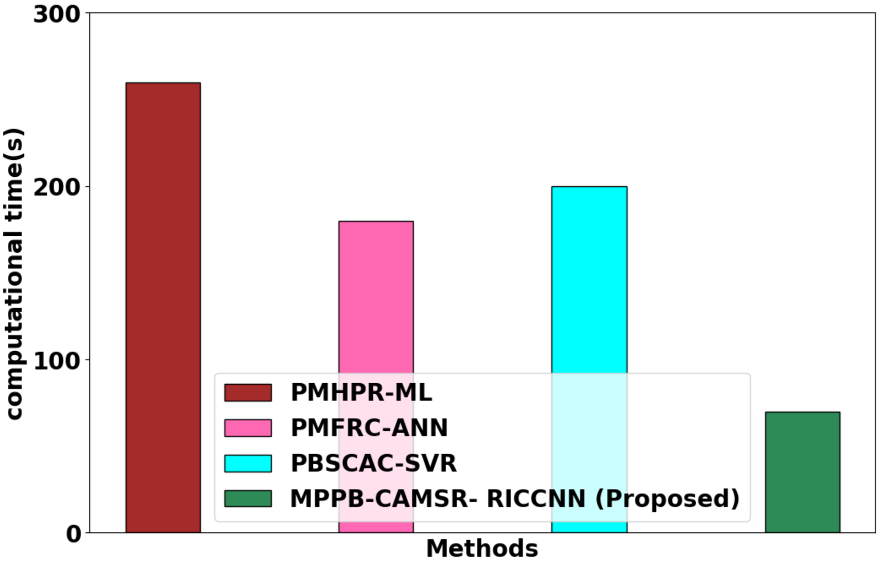

Figure 8: Performance Analysis of Computational Time

The presentation examination of Computational Period is depicted in figure 8. A computational time graph shows how long different models including PMHPR-ML, PMFRC-ANN and PBSCAC-SVR take to finish the training and prediction tasks for predicting HPFRCC using machine learning. In order to help choose the most time-effective model for real-world applications, the graph usually shows the models on the X-axis and the computational time (in seconds) on the Y-axis. This allows for a clear comparison of the resource requirements and efficiency of proposed MPPB-CAMSR-RICCNN model. The proposed MPPB-CAMSR-RICCNN method attains 23.58%, 20.23% and 27.12% lower mathematical time when compared with present methods like PMHPR-ML, PMFRC-ANN and PBSCAC-SVR respectively.

C. Discussion

The study introduces a novel MPPB-CAMSR-RICCNN method to accurately predict the mechanical properties crucial for seismic reinforcement HPFRCC. The regression functions pre-processing using MFIF and it clean the data from the collected dataset. Next, the data are fed to RICCNN to predict themechanical properties crucial for seismic reinforcement in HPFRCC, and then the optimization using BTGO is performed to optimize the weight parameters for RICCNN. The MPPB-CAMSR-RICCNN has high accuracy and recall evaluation metrics than existing methods. This holistic methodology ensures that the predictive models not only provide high accuracy but also maintain consistency across various performance metrics. The comparative analysis underscores the efficacy of the proposed method, highlighting its potential for practical applications in enhancing the seismic resistance of concrete structures. Future work may focus on extending this approach to other types of construction materials and further refining the optimization techniques to achieve even greater predictive performance.

IV. CONCLUSION

In conclusion, a novel approach, MPPB-CAMSR-RICCNN, for predicting mechanical properties crucial for seismic reinforcement in HPFRCC. By leveraging concrete microstructure data and advanced machine learning techniques, this method significantly outperforms existing approaches in terms of correctness, exactness, compassion, and specificity. The evaluation results demonstrate substantial improvements over established methods such as PMHPR-ML, PMFRC-ANN, and PBSCAC-SVR, with accuracy increases of 23.5%, 25.5%, and 24% respectively. Specifically, it showcases 25.03%, 22.53%, and 20.05% reductions in computation time, along with 28.5%, 27.5%, and 28% improvements in accuracy compared to other existing methods, demonstrating both enhanced efficiency and superior predictive performance. Additionally, higher precision, sensitivity, and specificity are achieved, highlighting the efficacy of the proposed approach in accurately predicting mechanical properties crucial for seismic reinforcement. As a future scope, exploring the integration of real-time sensor data into the predictive model could enhance its adaptability to dynamic structural conditions, further improving its accuracy and applicability in seismic reinforcement strategies. Additionally, investigating the scalability of the proposed approach to broader structural materials beyond HPFRCC could expand its utility across various construction contexts.

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