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Superb Fairy-Wren Optimized Lightweight Convolutional Refinement Network for Analyzing Generational Teaching Differences and Efficacy In Malappuram, Kerala

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Abstract

This study investigated the influence of generational teaching differences on educational efficacy within the Malappuram District, Kerala. Recognizing the limitations of existing deep learning models in analyzing these nuanced variations within a specific regional context, a Superb Fairy-wren Optimized Lightweight Convolutional Refinement Network (SFOA-optimized LCRN) was developed. This network captured complex and non-linear relationships within educational data to provide a robust framework for predicting teaching effectiveness. Optimization via the SFOA ensured efficient parameter tuning and enhanced model interpretability. Here, the data encompassing teacher demographics, survey responses detailing teaching methodologies, and quantitative measures of performance underwent rigorous preprocessing. This process included Multivariate Imputation by Chained Equations (MICE) for missing value imputation, Tanh-Estimator for outlier management, categorical data encoding through ordinal and one-hot encoding, textual data processing utilizing Natural Language Processing (tokenization, stemming, stop word removal), and numerical data normalization. The preprocessed data was analyzed through the SFOA-optimized LCRN to enable the identification of generational patterns along with the prediction of teaching effectiveness. The SFOA-optimized LCRN demonstrated significant performance improvements over existing models. Specifically, accuracy reached 99.7%, precision 98.95%, recall 98.87%, F1-score 98.91%, and specificity 99.02%. Furthermore, the model achieved an execution time of 91ms to highlight its computational efficiency. Practical recommendations, including tailored training programs, mentorship initiatives, and collaborative teaching strategies, were generated to address identified generational variations. These strategies aimed to foster an inclusive and technologically adaptive learning environment. The SFOA-optimized LCRN effectively analyzed generational teaching differences to lead to improved educational strategy development within the specified regional context.

Keywords: Lightweight Convolutional Refinement Network, Superb Fairy-wren Optimization Algorithm, Generational Differences (Teachers), Teaching-Learning Process, Educational Outcomes.

1. Introduction

A significant generational shift shapes the contemporary higher education landscape in Malappuram, Kerala. Student demographics have transitioned from predominantly Millennial (born approximately 1981–1996) to Generation Z (born approximately 1997–2012), demanding a critical reassessment of pedagogical practices [1]. This shift demands effective engagement with a cohort defined by digital immersion and distinct learning preferences [2-3]. Consequently, a systematic examination of generational differences in teaching methodologies and efficacy emerges [4]. The analysis explores experiences, perceptions, knowledge, and concerns regarding generative artificial intelligence (GenAI) integration [5]. A comparative study between Gen Z students and Gen X (born approximately 1965–1980) and Millennial (Gen Y) educators elucidates differing perspectives on GenAI implementation [6-7]. Intentions and concerns surrounding GenAI adoption in higher education are examined for both student and teacher populations [8]. Existing literature highlights substantial variations in teaching preferences, learning styles, technology use, and communication methods across generations [9]. Understanding these nuances is essential for responsible and effective GenAI integration. Additionally, identifying support structures for Gen X and Gen Y educators navigating technological advancements remains crucial [10].

Dynamic educational environments necessitate a thorough analysis of generational teaching differences and efficacy. Variations in technological proficiency and pedagogical philosophies across age groups require targeted interventions [11]. Effective technology integration and the adaptation of teaching methods to contemporary demands depend on a nuanced understanding of these generational distinctions [12]. Such analysis establishes a foundation for policy recommendations and resource allocation, ultimately enhancing educational quality. Additionally, a comprehensive examination informs the design of professional development programs. Tailored training initiatives address the specific needs and preferences of different age cohorts by ensuring effective knowledge transfer and skill enhancement [13-14]. This approach fosters a collaborative learning environment leveraging generational strengths to improve overall teaching efficacy. Data-driven insights further enable evidence-based strategies by promoting sustainable advancements in education [15].

Existing deep learning applications in educational research primarily focus on student performance prediction and personalized learning. Neural networks analyze student data, identify learning patterns, and develop adaptive learning systems. However, the direct application of deep learning to analyze generational teaching differences and efficacy remains limited. Current approaches lack the capacity to model complex interrelationships among demographic factors and teaching methodologies within specific regional contexts. Additionally, many deep learning models function as black boxes, limiting interpretability and hindering the extraction of actionable insights from model predictions. Understanding the underlying patterns and relationships between variables is essential for targeted educational interventions [16-21]. Therefore, transparent, and interpretable deep learning models are needed to facilitate meaningful analysis and informed decision-making.

The motivation for employing a Superb Fairy-wren Optimized Lightweight Convolutional Refinement Network arises from the necessity to capture intricate, non-linear relationships within complex educational data. Traditional analytical methods often fail to discern subtle patterns. The LCRN optimized by the SFOA provides a robust framework for modeling these relationships and predicting teaching effectiveness with enhanced precision. SFOA optimization capabilities ensure efficient parameter tuning, maximizing network performance and interpretability. The main contribution of Superb Fairy-wren Optimized Lightweight Convolutional Refinement Network for Analyzing Generational Teaching Differences and Efficacy in Malappuram, Kerala (SFOA-optimized LCRN for generational teaching efficacy analysis) are given below,

- Development of a Lightweight Convolutional Refinement Network (LCRN) for generational pattern analysis.
- Application of the Superb Fairy-wren Optimization Algorithm (SFOA) for enhanced LCRN network optimization.
- Implementation of a comprehensive data preprocessing pipeline, including Missing value imputation using Multivariate Imputation by Chained Equations (MICE); outlier management via Tanh-Estimator; categorical data encoding through ordinal and one-hot encoding; textual data processing utilizing Natural Language Processing (tokenization, stemming, stop word removal); and numerical data normalization.
- Generation of age-specific educational strategies based on identified generational differences.
- Provision of practical recommendations to improve teaching effectiveness in Malappuram, Kerala.

The research progresses through a structured sequence: Section 2 reviews literature survey, while Section 3 details the methodology, encompassing data collection, preprocessing including MICE imputation, Tanh-Estimator outlier handling, and NLP techniques and the core analysis employing a Superb Fairy-wren Optimized Lightweight Convolutional Refinement Network (LCRN) for generational pattern identification and teaching effectiveness prediction. Section 4 presents and interprets results by discussing implications for educational practice. Finally, Section 5 concludes the study, summarizing key results and suggesting future research avenues.

2. Literature Survey

This section provides a comprehensive review of recent advancements in analyzing generational differences in technology integration and their impact on teaching effectiveness in higher education. Some of the recent works are given below,

In 2023, Chan, C.K.Y. and Lee, K.K., et.al [16] proposed AI Generation Gap by exploring generational perceptions of generative AI in higher education with a focus on Gen Z students versus Gen X/Y teachers (AI generation gap). Through a survey-based workflow, data was gathered regarding experiences with perceptions and intentions. Gen Z students demonstrated optimism regarding AI's potential for efficiency with personalized learning. Teachers acknowledged benefits with concerns about overreliance and ethical implications as a distinct disadvantage noted in their feedback. By paralleling anticipated constraints of this approaches in discerning subtle data nuances, divergent adoption frequencies with anxieties across generations emerged.

In 2024, Arpaci, I., et.al., [17] suggested Multimodal Prediction of Teachers' Efficacy from structural equation modelling (SEM), Deep Learning, and artificial neural networks (ANN) Integration. Here, Cultural intelligence, motivation to teach, and culturally responsive classroom management self-efficacy predicted teacher's sense of efficacy. Structural equation modelling established linear relationships, while artificial neural networks and deep learning captured non-linear patterns. Sensitivity analysis identified culturally responsive classroom management self-efficacy as the most influential predictor. The multimodal approach, integrating structural equation modelling, deep learning, and artificial neural networks, provided a comprehensive understanding of teacher efficacy prediction. However, the models exhibited moderate accuracy.

In 2021, Szymkowiak, A., et.al., [18] proposed Information Technology and Gen Z by examining technology's impact on Gen Z knowledge acquisition with a specific focus on the role of teachers and the internet (Information technology and Gen Z). Through a survey-based workflow with ANOVA analysis, preferences were determined among 498 young people within an online learning community. Mobile applications with video content emerged as favored learning methods with an advantage reflecting Gen Z's digital fluency. However, it highlighted generational preferences within learning by mirroring the anticipated limitations in capturing the nuanced patterns of technology adoption with knowledge acquisition.

In 2022, Gomez, F.C., et.al [19] explores Teacher's Technology Integration Self-Efficacy by assessing confidence in technology use among urban K-12 teachers through an online survey aligned with ISTE standards. The workflow revealed a moderate average confidence level with a potential disadvantage in high-level integration. Through this quantitative study with professional development as a key factor, self-efficacy was established. However, it struggles with capturing the complex nuances of individual teacher experiences with a limitation in generalized findings.

In 2024, Panakaje, N., et.al., [20] proposed Revolutionizing Pedagogy by examining technology integration's impact on teacher learning with pedagogical strategies, performance, and student engagement within Karnataka's higher education. Through a mixed-method approach with a primarily quantitative focus via structured questionnaires, 700 faculty samples were analyzed with mediation and moderation. Technology integration significantly enhanced teacher learning with pedagogical strategies, which mediated improved performance with engagement. Institutional support further amplified these outcomes with a positive influence. However, relying on structured questionnaires presents a limitation with the ability to capture nuanced individual experiences with a disadvantage inherent in such methods with a potential loss of intricate data patterns.

In 2024, Zhai, X., [21] suggested Transforming Teacher's Roles by examining GenAI's impact on educators with a proposed framework of Observer, Adopter, Collaborator, and Innovator roles. This study explored perceptions with knowledge and practices by highlighting the need for teacher education to evolve alongside AI integration. Despite its comprehensive approach with structured categorization, limitations emerged in capturing individual teacher's fluid transitions between roles with a disadvantage in detecting intricate adoption patterns.

2.1 Problem Statement and Motivation

The rapid generational shift in Malappuram's higher education transitioning from Millennial to Gen Z students, necessitates a critical reassessment of pedagogical practices particularly in integrating Generative AI (GenAI). This study addresses the challenge of engaging a digitally immersed Gen Z cohort while navigating generational disparities in technological proficiency and pedagogical philosophies between Gen X/Y educators and Gen Z students [16-21]. Motivated by the limitations of existing deep learning applications in modeling complex interrelationships among demographic factors and teaching methodologies within this regional context, this research employs a Superb Fairy-wren Optimized Lightweight Convolutional Refinement Network (SFOA-optimized LCRN). The objective is to analyze generational teaching differences and efficacy by enabling the development of age-specific educational strategies and practical recommendations to enhance teaching effectiveness in Malappuram, Kerala.

3. Proposed Methodology

In this section, a comprehensive analysis of generational teaching differences and efficacy within Malappuram, Kerala is presented. The research commences with the collection of input data from teachers, that encompasses demographic information, survey responses detailing teaching methods, and quantitative measures of performance. Subsequently, a rigorous preprocessing phase addresses data quality through following steps such as Missing value imputation using Multivariate Imputation by Chained Equations (MICE); outlier management via Tanh-Estimator; categorical data encoding through ordinal and one-hot encoding; textual data processing utilizing Natural Language Processing (tokenization, stemming, stop word removal); and numerical data normalization. The core of the analysis involves a Lightweight Convolutional Refinement Network (LCRN). This network is optimized by the Superb Fairy-wren Optimization Algorithm (SFOA), which facilitates generational pattern analysis and teaching effectiveness prediction. The application of the SFOA ensures the LCRN operates with enhanced precision. Age-specific strategies enhanced teaching effectiveness, culminating in the delivery of optimized strategies directly addressing generational variations in Malappuram, Kerala, alongside practical recommendations including tailored training, mentorship, and collaborative teaching, to foster an inclusive, technologically adaptive environment. The block diagram of the proposed SFOA-optimized LCRN for generational teaching efficacy analysis is given in Figure 1. A thorough explanation of each component is given below,

3.1 Data collection

In this section, the data are collected for the analysis of generational teaching differences in Malappuram, Kerala through a mixed-methods approach that combines quantitative surveys with qualitative interviews. A structured questionnaire designed for capturing demographic information and teaching practices acted as the primary data collection tool. The survey targeted 200 teachers across primary, secondary, and higher education levels within the district.

Table 1: Dataset Structure for Generational Teaching Analysis

Feature Category	Feature Description	Data Type
Demographic Information	Age Group (25 and below, 26-40 (Millennial), 41-55 (Generation X), 56 and above (Baby Boomer))	Categorical
	Highest Level of Education (Bachelor's, Master's, Doctorate, Other)	Categorical
	Years of Teaching Experience (Less than 5, 5-10, 11-20, More than 20)	Ordinal
	Current Teaching Level (Primary, Secondary, Higher Education)	Categorical
Teaching Methodologies and Learning Outcomes	Preferred Teaching Style (Lecture-based, Interactive, Technology-integrated, Other)	Categorical
	Comfort with Adapting to New Methods (Very comfortable to Very uncomfortable)	Ordinal
	Frequency of Digital Tool Integration (Always to Never)	Ordinal
	Perceived Impact of Generational Diversity on Student Outcomes (Positive, Negative, No significant impact, Not sure)	Categorical
Advantages and Challenges of Generational Diversity	Perceived Advantage (Varied teaching styles, Exchange of experience, Increased adaptability, Other)	Categorical
	Experienced Challenges (Differences in teaching philosophies, Resistance to technology, Communication barriers, Differences in classroom management, Other)	Categorical (Multiple selection)
	Difficulty Collaborating (Yes, frequently to Never)	Ordinal
Adaptation to Technological Advancements and Innovation	Openness to Learning New Technology (Very open to Very resistant)	Ordinal
	Perceived Barriers to Adopting New Technology (Lack of training, Resistance to change, Time constraints, Limited access, Other)	Categorical
	Perceived Effectiveness of Professional Development (Very effective to Not effective at all)	Ordinal
Mentorship, Collaboration, and Professional Development	Belief in Mentorship Program Effectiveness (Yes, No, Not sure)	Categorical
	Collaboration Frequency with Different Generations (Regularly to Never)	Ordinal
General Opinions and Recommendations	Perceived Impact on Teaching-Learning Process (Positive, Negative, No significant impact, Not sure)	Categorical
	Recommendations for Improved Collaboration	Textual

Here, the questionnaire was distributed through educational institutions to ensure representation across generational cohorts. Responses were collected in a structured format for facilitating quantitative analysis. The table 1 provides a detailed outline of the dataset structure with the data organized into distinct feature categories for enabling subsequent analysis of generational differences in teaching practices. Interviews were conducted with a subset of teachers for providing qualitative insights into the challenges and benefits of generational diversity. The interview process delved into specific instances of intergenerational collaboration and conflict for giving context to the quantitative findings. This dual-method approach combined structured surveys with in-depth interviews for allowing a comprehensive examination of the research question.

3.2 Data Preprocessing

In this section, data processing addresses the necessity for transforming raw survey and interview data into a format suitable for analysis and modeling. Due to data inconsistencies, missing values, and variations in response formats within the initial dataset of 200 teacher responses, a systematic preprocessing phase was required. Data integrity was crucial for robust analytical outcomes through meticulous cleaning and transformation. Preprocessing began with the identification and handling of missing values. In this work, Multivariate Imputation by Chained Equations (MICE) is employed for Missing value imputation [22]. MICE generated multiple datasets through iterative imputation for analysis and pooling to reflect imputation uncertainty. Here Overall parameter estimates $\overline{\mathrm{P}}$ were calculated by averaging individual dataset parameters $\mathrm{DP_n}$. It is given in equation (1),

$$\overline{\mathrm{P}} = \frac{1}{\mathrm{z}} \times \sum_{\mathrm{n}=1} \mathrm{z} \times \mathrm{DP_n} \tag{1}$$

Where z is the number of imputed datasets. $\overline{\mathrm{P}}$ represents the overall (pooled) estimate of the parameter. $\mathrm{DP_n}$ is the parameter estimate from the $\mathrm{n^{th}}$ imputed dataset. Similarly, Overall variance $\overline{\mathrm{Var}}$ was computed using equation (2)

$$\overline{\mathrm{Var}} = \frac{1}{\mathrm{z}} \times \sum_{\mathrm{n}=1} \mathrm{z} \times \mathrm{Var_n} \tag{2}$$

Where $\overline{\mathrm{Var}}$ represents the overall (pooled) variance estimate. $\mathrm{Var_n}$ is the variance estimate from the $\mathrm{n^{th}}$ imputed dataset. Inter-dataset variability $\overline{\mathrm{A}}$ was determined by equation (3)

$$\overline{\mathrm{A}} = \frac{1}{\mathrm{z}-1} \times \sum_{\mathrm{n}=1} \mathrm{z} \times [\mathrm{DP_n} - \overline{\mathrm{P}}]^2 \tag{3}$$

This multivariate approach ensured robust handling of missing data by considering inter-variable dependencies across the following feature categories such as Demographic Information, Teaching Methodologies and Learning Outcomes, Advantages and Challenges of Generational Diversity, Adaptation to Technological Advancements and Innovation, Mentorship, Collaboration, and Professional Development & General Opinions and Recommendations.

Following missing value imputation with MICE, further preprocessing steps ensured data suitability for the Lightweight Convolutional Refinement Network. In this work, the tanh-estimator is employed for outlier detection [23]. It is defined in the equation (4)

$$\mathrm{Y_{transformed}} = \frac{1}{2}\left\{\tan\mathrm{h}\left[0.01\left(\frac{\mathrm{Y}-\mu_\mathrm{H}}{\sigma_\mathrm{H}}\right)\right] + 1\right\} \tag{4}$$

Where $\mathrm{Y_{transformed}}$ represents the transformed value. Y is the original data point. μ_H and σ_H are the mean and standard deviation calculated using Hampel estimators respectively. The Hampel estimator offered high efficiency and robustness by mitigating outlier influence, and is defined by Equation (5).

$$\psi(\mathrm{v}) = \begin{cases} \mathrm{v}; & 0 \\ \mathrm{p} \times \sin(\mathrm{v}); & \mathrm{p} \le |\mathrm{v}| < \mathrm{q} \\ \mathrm{p} \times \sin(\mathrm{v})\left[\frac{(\mathrm{r}-|\mathrm{v}|)}{(\mathrm{r}-\mathrm{q})}\right]; & \mathrm{q} \le |\mathrm{v}| < \mathrm{r} \\ 0; & \mathrm{r} \le |\mathrm{v}| \end{cases} \tag{5}$$

Where v is the data point. p, q and r are Hampel parameters. By this, tanh-estimator achieved robust normalization and enhanced statistical modeling by effectively addressing outliers.

Following robust outlier management, categorical data were initially in textual form before undergoing encoding for preparation in numerical analysis. Ordinal features representing ranked scales like "comfort level" and "frequency," were transformed into numerical values, for preserving their inherent order. Nominal features, such as "teaching style," were converted using one-hot encoding by generating binary columns for each unique category and thereby transforming single categorical variables into multiple numerical representations.

Following categorical data encoding, textual data sourced from surveys and interviews required Natural Language Processing (NLP). Tokenization, stemming, and stop word removal preprocessed the text by enabling subsequent sentiment and thematic analysis. Numerical features, such as years of experience and technology scores, underwent normalization with values scaled to a 0-1 range. This normalization ensured equal feature contribution to the Lightweight Convolutional Refinement Network. These preprocessing steps ensured the data's compatibility and facilitated effective network training and analysis.

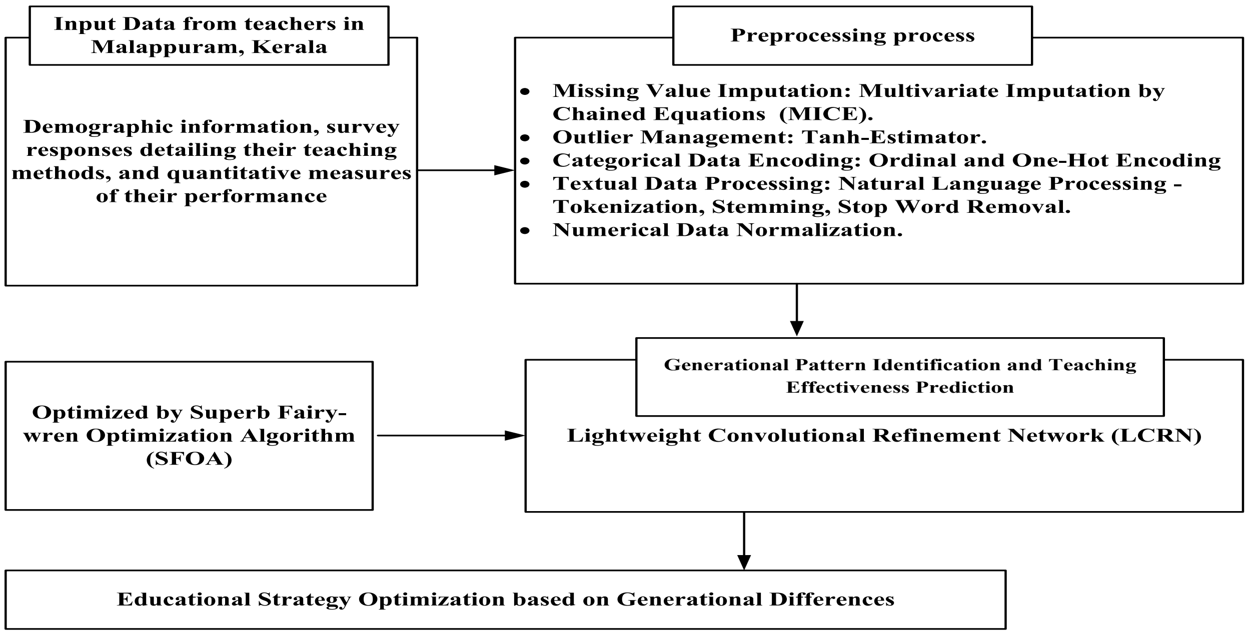

Figure 1: Block diagram for Proposed SFOA-optimized LCRN for generational teaching efficacy analysis

3.3 Generational Pattern Identification and Teaching Effectiveness Prediction via SFOA-Optimized LCRN

This section discusses the application of the Superb Fairy-wren Optimized Lightweight Convolutional Refinement Network (SFOA-optimized LCRN) to achieve accurate identification of generational teaching patterns and improve the prediction of teaching effectiveness within Malappuram, Kerala. At its core, the analytical process employed a Lightweight Convolutional Refinement Network (LCRN). This network architecture is chosen for its efficiency in managing intricate data patterns while processing the preprocessed dataset. The LCRN's function involved the extraction of pertinent features and the modeling of correlations between teacher demographics and teaching methodologies. To augment the LCRN's performance, the Superb Fairy-wren Optimization Algorithm (SFOA) optimized the network's parameters. This bio-inspired algorithm iteratively refined the LCRN's weights and biases. This optimization procedure enabled the precise identification of generational patterns and improved the accuracy of teaching effectiveness predictions. The SFOA's implementation ensured the LCRN operated with heightened precision, that results in robust and reliable analysis of educational data. Consequently, the network architecture and optimization algorithm functioned collaboratively by generating detailed insights into generational teaching differences.

The Lightweight Convolutional Refinement Network (LCRN) adapts deep learning principles to analyze generational teaching patterns and predict effectiveness. It employs a specialized architecture focused on efficient feature extraction and prediction, which is crucial for processing pre-processed educational data for estimating teaching effectiveness and generational pattern classification. The LCRN distinguishes itself by utilizing depth wise separable convolutions (DSC), feature attention (F) blocks, and residual blocks (R) to refine input data related to teacher demographics and methodologies [24]. The network architecture is structured into two primary sections such as feature extraction and prediction is given in Figure 2. The feature extraction phase begins with a 2D CNN followed by batch normalization (BN) and ReLU activation. Subsequent refinement involves a series of DSC blocks. DSC reduces computational load by separating standard convolution into depth wise and pointwise operations. Depthwise Convolution ($\mathrm{Dpt_{Conv}}$) applies a single filter per input channel is represented using equation (6)

$$\mathrm{Dpt_{Conv}}(\mathrm{Kernel}, \mathrm{F})_{x,y,z} = \sum_{kh,kw} \mathrm{Kernel}_{kh,kw} \times \mathrm{F}_{x+kh,y+kw,z} \quad (6)$$

Where Kernel is the convolution kernel, F is the input feature map, x, y and z are feature map indices, and kh and kw are kernel indices. Pointwise Convolution ($\mathrm{P_{Conv}}$) combines $\mathrm{Dpt_{Conv}}$ outputs via 1×1 convolutions using equation (7)

$$\mathrm{P_{Conv}}(\mathrm{Kernel}, \mathrm{F})_{x,y} = \sum_{z} \mathrm{Kernel}_{z} \times \mathrm{F}_{x,y,z} \quad (7)$$

Here, Kernel represents the 1×1 convolution kernel. To enhance feature granularity, F blocks are incorporated. These blocks capture relationships between local features through average and max pooling operations. The pooled features are concatenated and processed by a 2D convolution with a sigmoid activation function by generating a spatial attention map. This process is defined using equation (8-11)

$$F_{\text{average pooling}} = \text{Average pooling }(F) \quad (8)$$

$$F_{\text{Max pooling}} = \text{Max pooling }(F) \quad (9)$$

$$SA(F) = \varphi\left[C_{3\times3}\left(F_{\text{average pooling}} \oplus F_{\text{Max pooling}}\right)\right] \quad (10)$$

$$F^{*} = F \times SA(F) \quad (11)$$

Where φ is the sigmoid function, $C_{3\times3}$ is a 3×3 convolution, and $\oplus$ is the concatenation operator. This attention mechanism allows the network to focus on relevant features by improving the accuracy of generational pattern identification.

Residual blocks (R) mitigate the vanishing gradient problem by enabling the training of deeper networks. R consists of convolutional layers, BN, and LeakyReLU activation. The LeakyReLU activation addresses potential issues with ReLU when negative values are present. The residual block's operation is expressed using equation (12-13)

$$\ddot{I} = I \oplus \text{ out} \quad (12)$$

$$\text{Leaky ReLU }[\ddot{I}] = \begin{cases} 1; & \text{if } \ddot{I} > 0 \\ \aleph; & \text{Otherwise} \end{cases} \quad (13)$$

WhereI is the input, out is the layer's output, $\oplus$ is concatenation, $\ddot{I}$ is the concatenated input, and $\aleph$ is the leakage factor. The prediction section utilizes global average pooling, dropout, dense layers, and softmax to estimate teaching effectiveness and generational pattern classification. This architecture facilitates the identification of generational teaching patterns and the prediction of teaching effectiveness within educational datasets by effectively managing complex data.

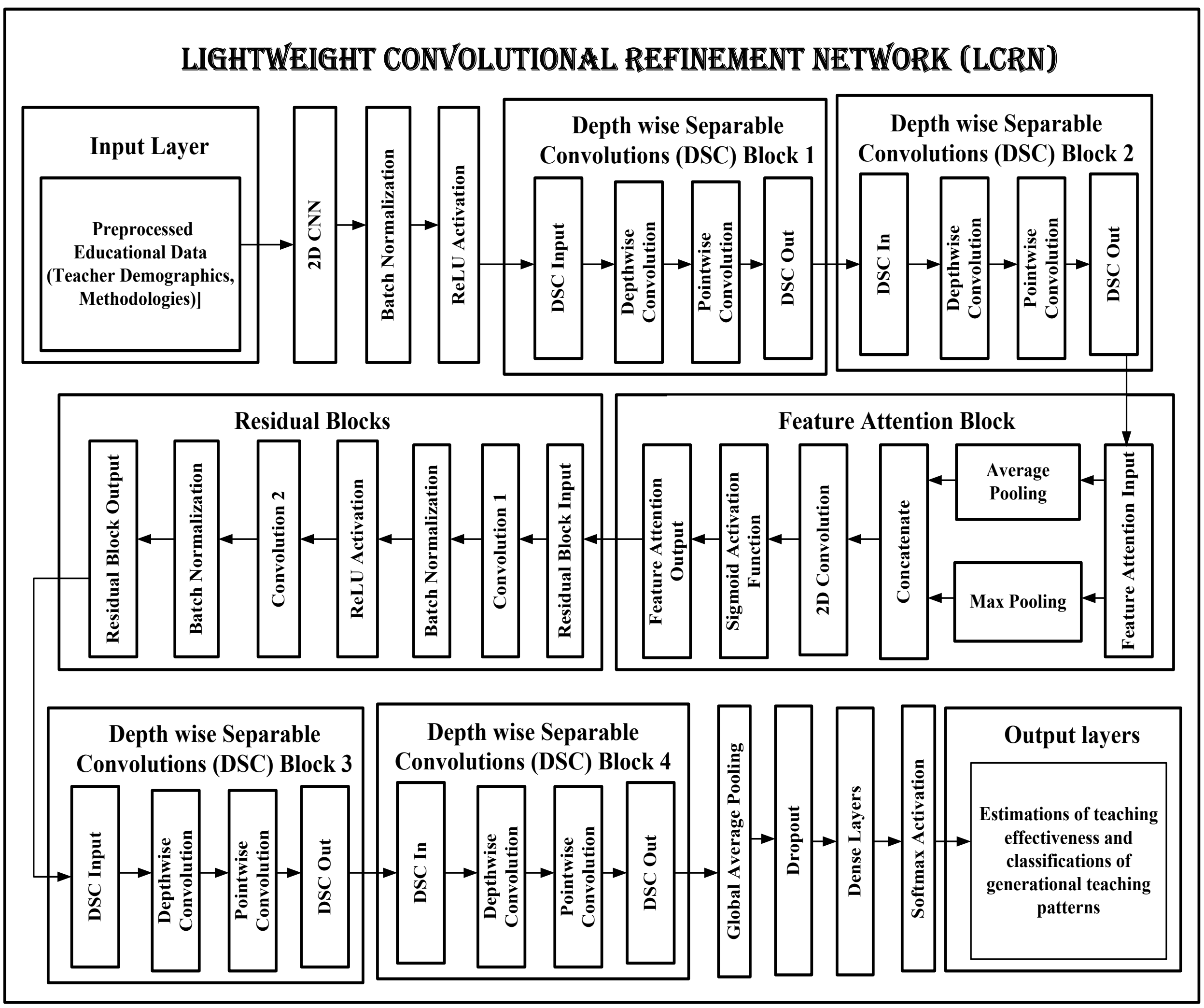

Figure 2: Architecture of the Lightweight Convolutional Refinement Network (LCRN)

After this, Superb Fairy-wren Optimization Algorithm (SFOA) enhances the Lightweight Convolutional Refinement Network (LCRN) by optimizing its weights and biases parameters. This optimization refines the LCRN network's ability to identify generational teaching patterns and predict teaching effectiveness. SFOA is a bio-inspired algorithm, that mimics the natural behaviors of superb fairy-wrens [25]. It is given in algorithm 1. The algorithm's operation initiates with population initialization. Each member representing a candidate solution is defined by a vector. The global matrix G comprises these vectors, where G_m denotes the m^{th} member, and $g_{m\times dim}$ represents the dim^{th} dimension of G_m using equation (14)

$$G = \begin{bmatrix} G_1 \\ \vdots \\ G_m \\ \vdots \\ G_S \end{bmatrix}_{S\times dim} \tag{14}$$

Initialization occurs using equation (15)

$$G = [UB - LB] \times R(0,1) + LB \tag{15}$$

where UB and LB are the upper and lower bounds of the decision variables, and R(0,1) generates a random number between 0 and 1. The algorithm progresses through three phases such as young bird growth, breeding and feeding, and predator avoidance. The Young Bird Growth Stage simulates the rapid growth of young birds by facilitating extensive exploration. New member positions are calculated using equation (16)

$$G\,new_{p,q} = G_{p,q}^{t} + \{LB + [[UB - LB] \times R]\},\ R>0.5 \tag{16}$$

where $G\,new_{p,q}$ is the new position, $G_{p,q}^{t}$ is the position at iteration t, and R generates a random number. After this, Breeding and Feeding Stage models the teaching behavior during breeding. A danger threshold k determines entry into this phase using equation (17)

$$k = R_1 \times 20 + R_2 \times 20 \tag{17}$$

where R_1 and R_2 are normally distributed random numbers. Then, Member positions update using equation (18-19)

$$G\,new_{p,q} = G_B + [G_{OP} \times G_{p,q}^{t}] \times u, R < 0.5 \text{ and } k < 20 \tag{18}$$

$$G_B = G_{OP} \times \rho \tag{19}$$

where G_{OP} is the current optimal position and constant ρ with a value of 0.8, and u is a factor related to the teaching cycle using equation (20)

$$u = \sin[(UB - LB) \times 2 + (UB - LB) \times j] \tag{20}$$

where j represents the teaching cycle using equation (21)

$$j = \left[\frac{E}{Max\ E}\right] \times 2 \tag{21}$$

Where, E is the current number of evaluations, and Max E is the maximum number of evaluations. Then, Predator Avoidance Stage models the defense mechanism against predators. Member positions update using equation (22)

$$G\,new_{p,q} = G_{OP} + G_{p,q} \times levy \times AFBF, R < 0.5 \text{ and } k > 20 \tag{22}$$

where levy is the Levy flight random step size, and AFBF is an adaptive flight balance factor using equation (23)

$$AFBF = 0.2 \times \sin\left[\frac{\pi}{2} - c\right] \tag{23}$$

where c is the call frequency value using equation (24)

$$c = \left[\frac{E}{Max\ E}\right] \times \frac{\pi}{2} \tag{24}$$

The algorithm combines these stages into a unified update rule using equation (25)

$$G\,new_{p,q} = \begin{cases} G_{p,q}^{t} + \{LB + [[UB - LB] \times R]\}, R > 0.5 \\ G_{OP} \times \rho + [G_{OP} - G_{p,q}^{t}] \times u, R < 0.5 \text{ and } k > 20 \\ G_{OP} + G_{p,q} \times levy \times AFBF, R < 0.5 \text{ and } k < 20 \end{cases} \tag{25}$$

This process iteratively refines the LCRN's parameters through improved accuracy in generational pattern identification and teaching effectiveness prediction.

Algorithm 1: Bio-inspired SFOA algorithm for generational pattern identification and teaching effectiveness prediction
Step 1: Initialize population G using equation (15)
Step 2: For each member G_m, update position based on young bird growth using equation (16)
Step 3: Calculate danger threshold k using equation (17)
Step 4: If $R < 0.5$ and $k < 20$, update position using equation (18) and u is a factor related to the teaching cycle using equation (20)
Step 5: Calculate j represents the teaching cycle using equation (21)

Step 6: If $R < 0.5$ and $k > 20$, update position using equation (22)
Step 7: Calculate adaptive flight balance factor AFBF using equation (23)
Step 8: Calculate call frequency c using equation (24)
Step 9: Apply unified update rule using equation (25).
Step 10: Repeat steps 2-9 until termination criteria are met.

Following analysis, the SFOA-optimized LCRN also provided recommendations. Tailored training programs addressed age-specific technology adoption needs. Mentorship initiatives paired experienced teachers with younger educators for knowledge exchange. Collaborative teaching strategies encouraged intergenerational teamwork, that leverages diverse teaching strengths. This study highlighted strategies for creating an inclusive and technologically adaptive teaching-learning environment, that contributes to research on generational influences in education.

4. Results And Discussion

In this, performance of the Superb Fairy-Wren Optimized Lightweight Convolutional Refinement Network for Analyzing Generational Teaching Differences and Efficacy in Malappuram, Kerala (SFOA-optimized LCRN) is evaluated. Generational teaching difference data is partitioned according to a 3:1:1 ratio for training, validation, and testing. Experiments are conducted on an Intel Core i7 processor at 2.50 GHz with 8 GB RAM, running Windows 10. The SFOA-optimized LCRN is implemented in Python. This section presents a comparative analysis of the proposed framework against established methods like AI generation gap [16], ANN [17] and Information technology and Gen Z [18] respectively.

4.1 Performance Metrics

The performance evaluation involves several key metrics are given below,

Accuracy: It represents ratio of correct generational teaching difference predictions to total predictions. It is computed using equation (26).

$$\text{Accuracy} = \frac{\text{TP}+\text{TN}}{\text{TP}+\text{FP}+\text{TN}+\text{FN}} \tag{26}$$

Where True Positive (TP) denotes correctly predicted instances of generational teaching efficacy or differences; True Negative (TN) specifies correctly predicted instances of absence of generational teaching efficacy or differences; False Positive (FP) epitomizes instances where absence of generational teaching efficacy or differences is incorrectly predicted; False Negative (FN) implies instances where generational teaching efficacy or differences is incorrectly predicted as absent.

Precision: It indicates proportion of positive generational teaching difference predictions that are correct. It is computed using equation (27).

$$\text{Precision} = \frac{\text{TP}}{(\text{TP}+\text{FP})} \tag{27}$$

Recall: It measures proportion of actual positive generational teaching difference identified correctly. It is computed using equation (28).

$$\text{Recall} = \frac{\text{TP}}{(\text{TP}+\text{FN})} \tag{28}$$

F1 Score: It represents harmonic mean of precision and recall. It is computed using equation (29).

$$\text{F1 Score} = \frac{2\times(\text{Precision}\times\text{Recall})}{(\text{Precision}+\text{Recall})} \tag{29}$$

Specificity: It measures proportion of actual negatives correctly identified. It is computed using equation (30).

$$\text{Specificity} = \frac{\text{TN}}{(\text{TN}+\text{FP})} \tag{30}$$

Execution Time: It represents computational resource consumption of the model measured in seconds or milliseconds.

4.2 Performance Analysis

Figures 3-8 present a comparative analysis of SFOA-optimized LCRN against AI generation gap [16], ANN [17] and Information technology and Gen Z [18] respectively.

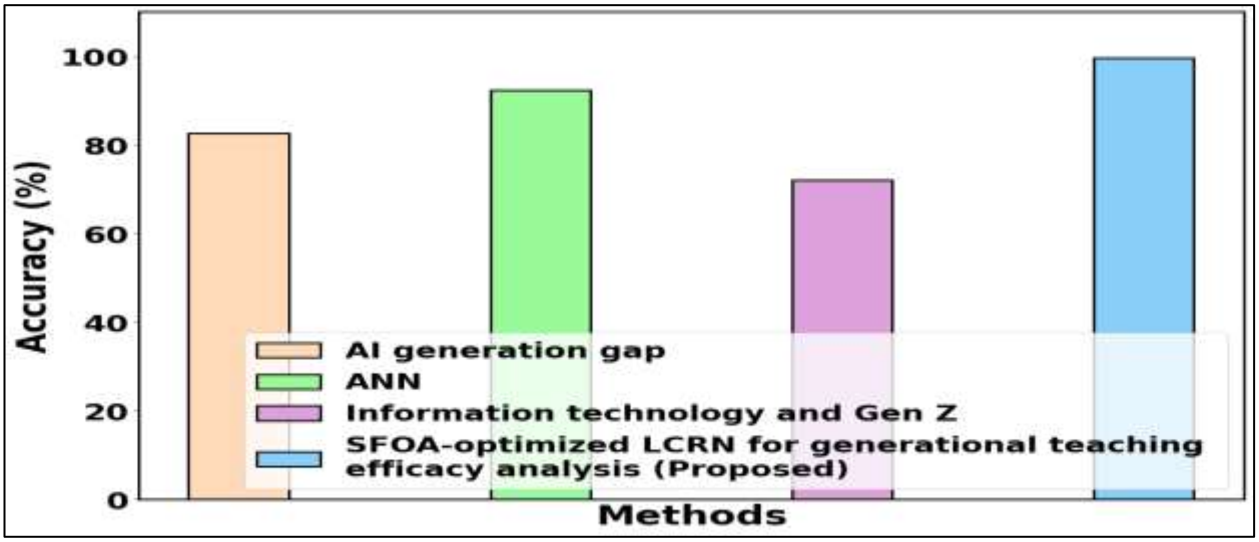

Figure 3: Accuracy analysis

Figure 3 presents a comparative analysis of accuracy across various predictive models. The Superb Fairy-wren Optimization Algorithm (SFOA)-optimized Lightweight Convolutional Refinement Network (LCRN) demonstrates a significant performance advantage. Specifically, the proposed methodology achieves a 20.59% accuracy improvement relative to the AI generation gap model, a 7.97% increase over the Artificial Neural Network (ANN) model, and a substantial 38.47% enhancement compared to the Information Technology and Gen Z model. These numerical differences highlight the SFOA-LCRN's superior ability to model and predict teaching effectiveness based on generational differences. The observed accuracy gains suggest a more nuanced and effective capture of underlying patterns within the educational dataset, that ultimately leads to more reliable predictions. The substantial margins of improvement indicate the robustness and precision of the SFOA-LCRN approach by demonstrating its potential for practical application in educational strategy optimization.

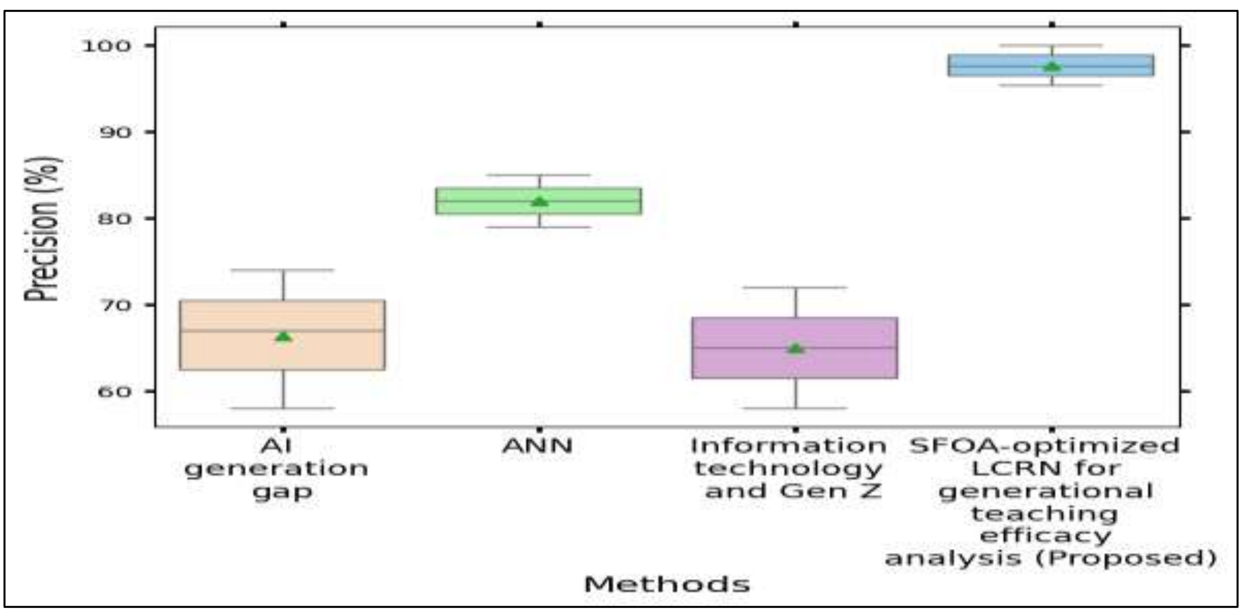

Figure 4: Precision analysis

Figure 4 illustrates the precision outcomes across the evaluated methodologies. The Superb Fairy-wren Optimization Algorithm (SFOA)-optimized Lightweight Convolutional Refinement Network (LCRN) exhibits a marked improvement in precision. Quantitatively, the proposed method yields a 47.68% precision increase over the AI generation gap model, a 19.21% elevation compared to the Artificial Neural Network (ANN) model, and a 54.609% surge relative to the Information Technology and Gen Z model. These numerical values underscore the SFOA-LCRN's refined ability to identify relevant positive instances. The demonstrated precision gains signify a reduced rate of false positives, thereby enhancing the reliability of the model's predictions. The observed high precision values attest to the method's effectiveness in accurately classifying teaching effectiveness based on generational disparities.

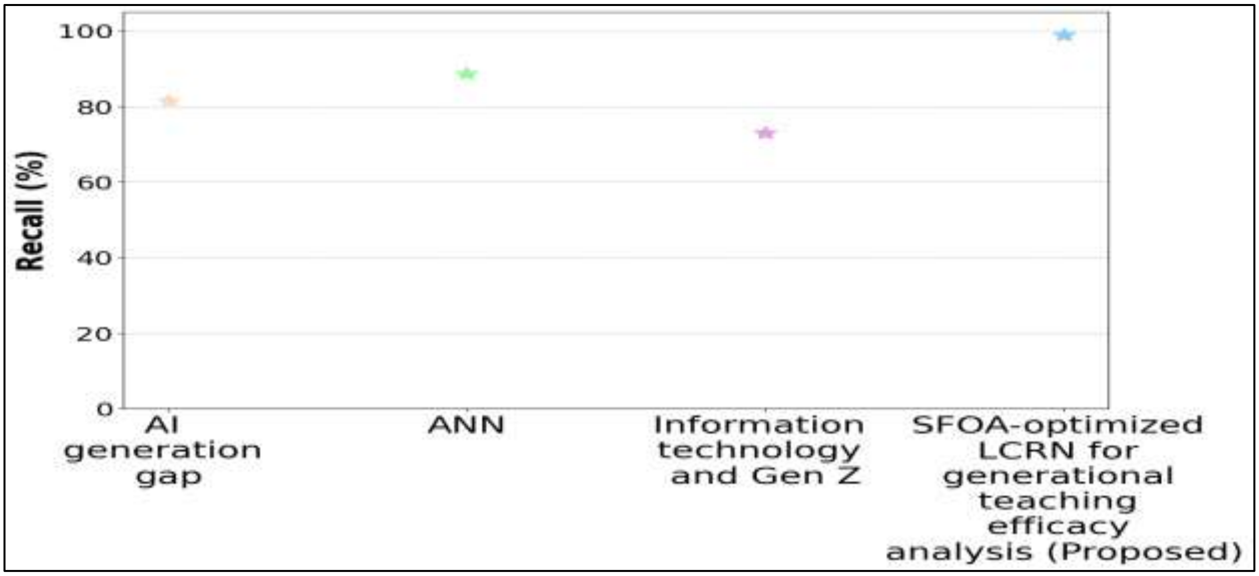

Figure 5: Recall analysis

Figure 5 presents the recall performance of the analyzed models. The Superb Fairy-wren Optimization Algorithm (SFOA)-optimized Lightweight Convolutional Refinement Network (LCRN) displays a notable improvement in recall. Specifically, the proposed method achieves a 21.38% increase in recall compared to the AI generation gap model, an 11.503% rise over the Artificial Neural Network (ANN) model, and a 35.401% enhancement relative to the Information Technology and Gen Z model. These figures indicate the SFOA-LCRN's heightened capacity to capture all relevant positive instances. The demonstrated recall gains highlight a reduction in false negatives by signifying a more comprehensive identification of effective teaching strategies across generations. The observed high recall values affirm the model's ability to minimize missed relevant data, thus providing a more complete picture of teaching effectiveness.

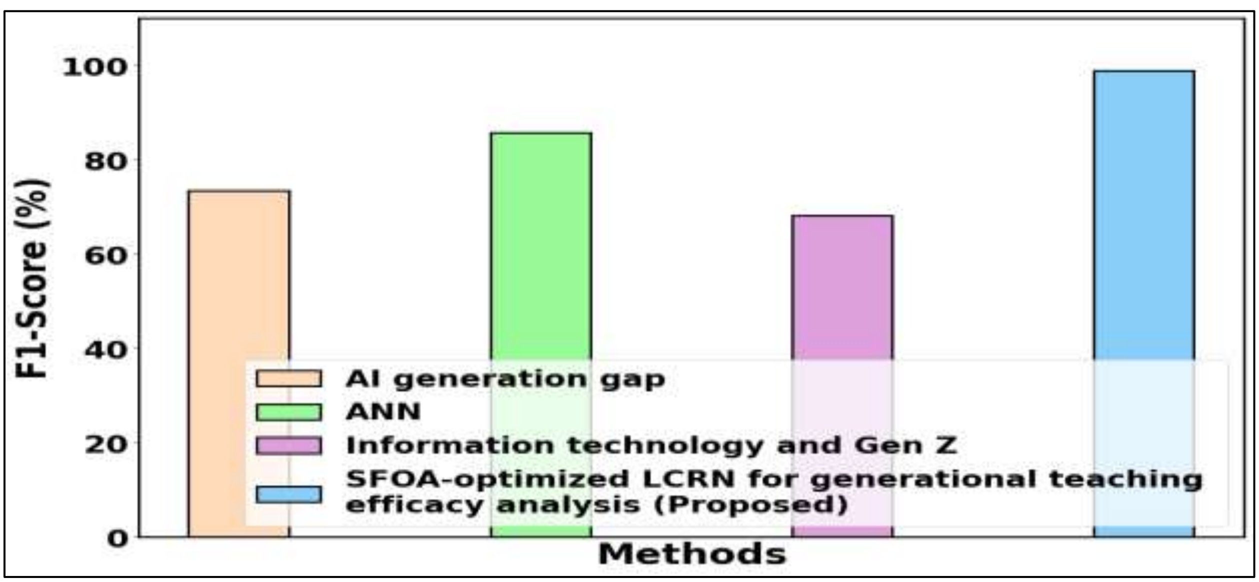

Figure 6: F1-Score analysis

Figure 6 illustrates the F1-Score comparison among the evaluated models. The Superb Fairy-wren Optimization Algorithm (SFOA)-optimized Lightweight Convolutional Refinement Network (LCRN) demonstrates a substantial improvement in F1-Score. Specifically, the proposed methodology achieves a 34.53% increase relative to the AI generation gap model, a 15.35% elevation over the Artificial Neural Network (ANN) model, and a 45.001% surge compared to the Information Technology and Gen Z model. These numerical values signify the SFOA-LCRN's balanced performance in both precision and recall. The high F1-Score values confirm the model's ability to provide accurate and comprehensive assessments of teaching effectiveness across generational differences.

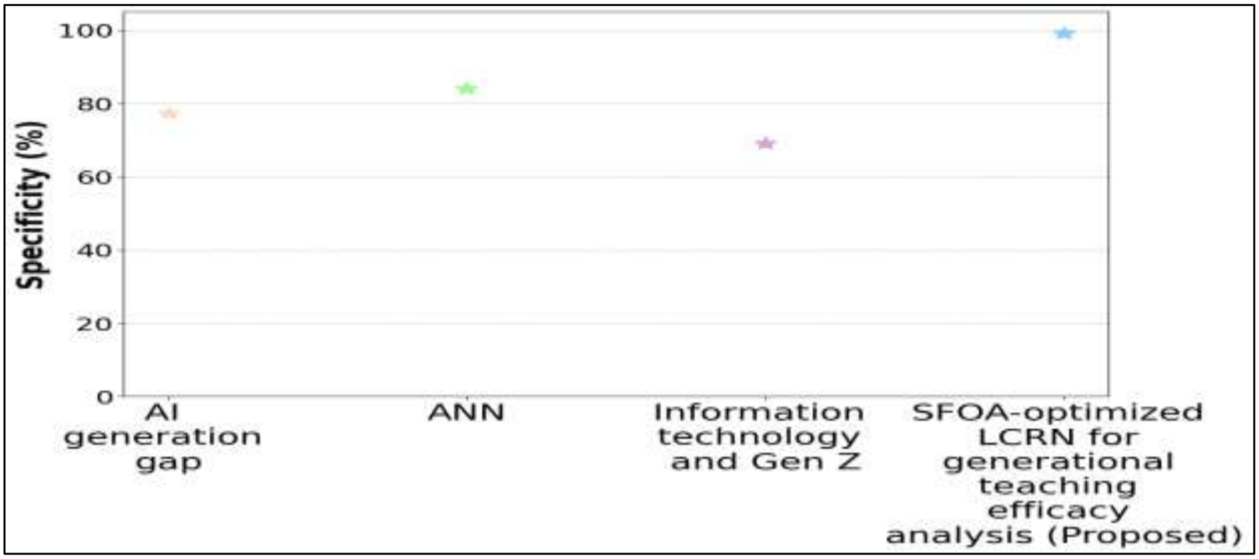

Figure 7: Specificity analysis

Figure 7 demonstrates the specificity outcomes of the assessed models. The Superb Fairy-wren Optimization Algorithm (SFOA)-optimized Lightweight Convolutional Refinement Network (LCRN) exhibits a prominent improvement in specificity. Quantitatively, the proposed method yields a 28.21% increase in specificity compared to the AI generation gap model, a 17.78% elevation over the Artificial Neural Network (ANN) model, and a 43.46% surge relative to the Information Technology and Gen Z model. These numerical values emphasize the SFOA-LCRN's enhanced ability to correctly identify negative instances. The demonstrated specificity gains signify a reduced rate of false positives in negative classifications, thereby improving the model's reliability in identifying ineffective teaching strategies. The observed high specificity values confirm the method's effectiveness in accurately distinguishing between negative and positive cases, that contributes to a more precise evaluation of teaching effectiveness across generational differences.

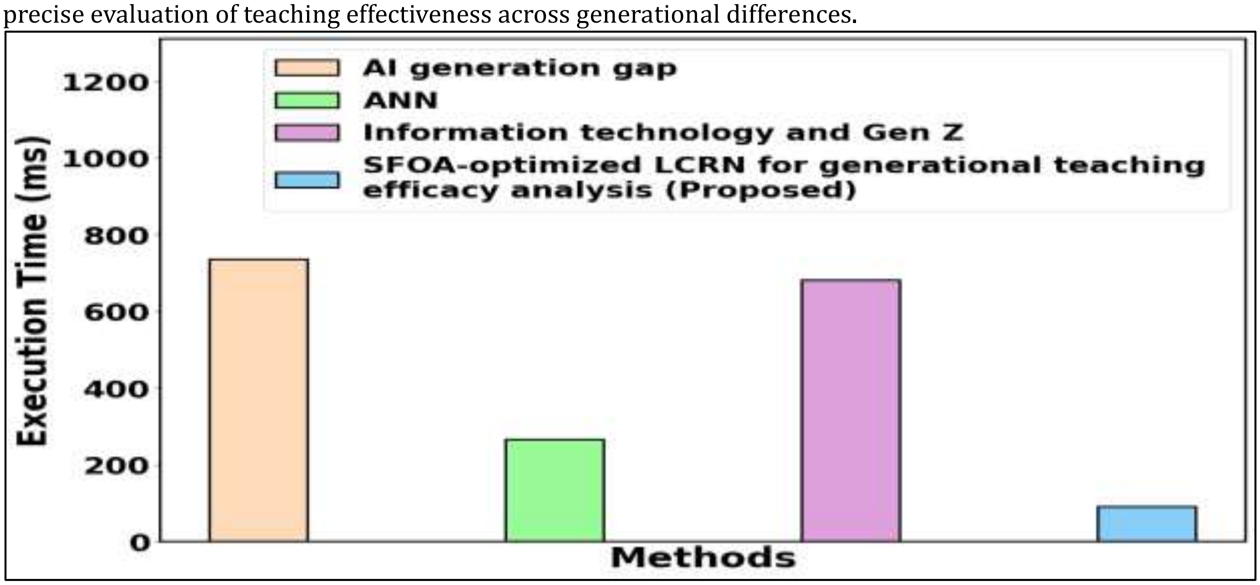

Figure 8: Execution Time analysis

Figure 8 details the computational efficiency of the evaluated methodologies. The Superb Fairy-wren Optimization Algorithm (SFOA)-optimized Lightweight Convolutional Refinement Network (LCRN) demonstrates a substantial reduction in execution time. Quantitatively, the proposed method achieves an 87.61% decrease in processing time compared to the AI generation gap model, a 65.91% reduction relative to the Artificial Neural Network (ANN) model, and an 86.65% decrease compared to the Information Technology and Gen Z model. These numerical values underscore the SFOA-LCRN's optimized computational performance. The observed decrease in execution time highlights the method's efficiency in processing data and generating predictions. The significantly lower execution times indicate the model's suitability for deployment in time-sensitive applications, that reveals its practical advantage in real-world educational strategy optimization scenarios.

4.3 Discussion

The developed Superb Fairy-wren Optimized Lightweight Convolutional Refinement Network (SFOA-optimized LCRN) demonstrates a substantial improvement in analyzing generational teaching differences and efficacy within the Malappuram, Kerala context. The network's performance, as evidenced by significant gains in accuracy, precision, recall, F1-score, and specificity, underscores its effectiveness in capturing complex interrelationships among demographic factors and teaching methodologies. It is given in Figure 3-8 and Table 2. The proposed SFOA-optimized LCRN method attains 20.59%, 7.97% and 38.47% higher accuracy; 47.68%, 19.21% and 54.609% higher precision; 21.38%, 11.503% and 35.401% higher recall; 34.53%, 15.35% and 45.001% higher F1-Score and 28.21%, 17.78% and 43.46% higher Specificity against AI generation gap, ANN and Information technology and Gen Z respectively. The optimization of the LCRN using the Superb Fairy-wren Optimization Algorithm (SFOA) contributes to a more nuanced and precise modeling of these relationships, leading to enhanced prediction capabilities.

Table 2: Performance Evaluation of Different Models for Generational Teaching Efficacy Analysis

	AI generation gap [16]	**ANN [17]**	**Information technology and Gen Z [18]**	**SFOA-optimized LCRN for generational teaching efficacy analysis (Proposed)**
Accuracy (%)	82.67	92.34	72	99.7
Precision (%)	67	83	64	98.95
Recall (%)	81.45	88.67	73.02	98.87
F1-Score (%)	73.52	85.74	68.21	98.91
Specificity (%)	77.23	84.07	69.02	99.02
Execution Time (ms)	735	267	682	91

The rigorous data preprocessing pipeline, incorporating MICE for missing value imputation, Tanh-Estimator for outlier management, ordinal and one-hot encoding for categorical data, NLP for textual data, and normalization for numerical data, ensures data quality and consistency. This comprehensive approach facilitates the extraction of meaningful patterns from the educational dataset. The significant reduction in execution time achieved by the SFOA-optimized LCRN highlights its computational efficiency. This efficiency is crucial for real-world applications, where timely analysis and deployment are essential. The model's ability to provide age-specific educational strategies and practical recommendations demonstrates its potential for improving teaching effectiveness within the specific regional context of Malappuram, Kerala. The comparative analysis against existing models, specifically the AI generation gap model, Artificial Neural Network (ANN) model, and Information Technology and Gen Z model, consistently reveals the superior performance of the proposed SFOA-optimized LCRN. The substantial performance gains across all evaluation metrics validate the model's robustness and precision. The ability to minimize false positives and negatives, as reflected in the high precision and recall values, that ensures the reliability and comprehensiveness of the model's predictions. Following analysis, the SFOA-optimized LCRN also provided recommendations. Tailored training programs addressed age-specific technology adoption needs. Mentorship initiatives paired experienced teachers with younger educators for knowledge exchange. Collaborative teaching strategies encouraged intergenerational teamwork, that leverages diverse teaching strengths. This study highlighted strategies for creating an inclusive and technologically adaptive teaching-learning environment, that contributes to research on generational influences in education.

Future development focuses on enhancing the SFOA-optimized LCRN's interpretability and accessibility. Integration of explainable AI (XAI) techniques provides insight into model predictions, fostering trust and enabling the extraction of actionable knowledge for educators and policymakers. A user-friendly interface or application simplifies model deployment, that will facilitate the implementation of age-specific educational strategies and the continuous monitoring of teaching effectiveness. Expanding the model to incorporate multimodal data, specifically classroom observation videos and student engagement metrics, enriches the analysis. This multimodal approach uncovers subtle patterns and relationships, that yields a more comprehensive understanding of teaching efficacy beyond traditional data limitations.

5. Conclusion

This research presented a comprehensive analysis of generational teaching differences and efficacy within Malappuram, Kerala. In this study, the initial data encompassed teacher demographics along with survey responses and underwent rigorous preprocessing. The preprocessing included MICE for missing value imputation, along with the Tanh-Estimator for outlier management, categorical data encoding for structured representation, NLP for textual data processing, and numerical data normalization to ensure data quality. A Lightweight Convolutional Refinement Network (LCRN), which was optimized through the Superb Fairy-wren Optimization Algorithm (SFOA) analyzed the preprocessed data. The SFOA optimization enhanced the precision of the LCRN in generational pattern analysis and teaching effectiveness prediction. Following analysis, the SFOA-optimized LCRN also provided recommendations. Tailored training programs addressed age-specific technology adoption needs. Mentorship initiatives paired experienced teachers with younger educators for knowledge exchange. Collaborative teaching strategies encouraged intergenerational teamwork, that leverages diverse teaching strengths. This study highlighted strategies for creating an inclusive and technologically adaptive teaching-learning environment, that contributes to research on generational influences in education. Age-specific educational strategies along with practical recommendations derived from the analysis directly addressed generational variations in teaching effectiveness. The model's performance validated its robustness along with its precision in capturing complex interrelationships between demographic factors and teaching methodologies. The SFOA-optimized LCRN demonstrated substantial improvements over existing models, including AI Generation Gap, ANN, and Information Technology and Gen Z, across accuracy by 20.59%, 7.97%, and 38.47%, along with precision by 47.68%, 19.21%, and 54.609%, recall by 21.38%, 11.503%, and 35.401%, F1-score by 34.53%, 15.35%, and 45.001%, and specificity by 28.21%, 17.78%, and 43.46%. The model achieved significant reductions in execution time by 87.61%, 65.91%, and 86.65%, which highlighted its computational efficiency.

For future development, the focus will be on enhanced interpretability along with accessibility. The integration of explainable AI (XAI) techniques will provide insight into model predictions to foster trust and enable the extraction of actionable knowledge. A user-friendly interface or application will be developed for simplifying model deployment to facilitate the implementation of age-specific educational strategies along with continuous monitoring of teaching effectiveness. The expansion of this study will incorporate multimodal data, including classroom observation videos along with student engagement metrics to enrich the analysis. This multimodal approach will uncover subtle patterns along with relationships to yield a more comprehensive understanding of teaching efficacy beyond traditional data limitations.

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