Investigation of Chat GPT's Impact on Education Using Deep Spectral-Spatial Residual Attention Networks

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Abstract: *The revolutionary influence of powerful generative models, such as Chat Generative Pre-trained Transformer (ChatGPT) and mid-journey is causing significant changes in the higher education setting. These models examine the future of education and its potential to completely transform the way to teach and learn and have far-reaching implications. In this paper, investigation of ChatGPT's impact on education using Deep Spectral-Spatial Residual Attention Networks (DSSRAN-CGPT) is proposed. Initially, the input data is amassed from ChatGPT sentiment analysis dataset. The input data is pre-processed using Continuous-discrete Derivative-free Extended Kalman Filter (CDFEKF) to remove the unwanted data from the collected input data; then the pre-processed data are fed to feature extraction using Synchro-Transient-Extraction Transform (STET) to extract the statistical features, like energy, standard deviation, variance and kurtosis. Then the extracted features are supplied to the DSSRAN for effectively classifying the positive sentiment, negative sentiment and neutral sentiment. Generally, DSSRAN does not adapt any optimization approaches to determine the optimal parameters to ensure accurate classification of ChatGPT in education. Hence, Parrot Optimization Algorithm (POA) is proposed to optimize the DSSRAN, which accurately classifies the ChatGPT in education. The performance metrics, like accuracy, precision, recall, specificity, F1-score, computation time and Receiver Operating Characteristic curve (ROC) are analyzed. The performance of the proposed DSSRAN-CGPT approach attains 97% accuracy; 92% higher precision and 75% lower computation time when compared to the existing methods, like exploring the impact of ChatGPT in education: A web mining including machine learning approach (CGPT-ELA), unlocking the opportunities through ChatGPT Tool towards improving the education system (CGPT-AES) and ChatGPT in education: A discourse analysis of Worries and Concerns on Social-Media (CGPT-WCSM).*

Keywords: *Chat generative pre-trained transformer, continuous-discrete derivative-free extended Kalman filter, deep spectral-spatial residual attention network, parrot optimization algorithm, synchro-transient- extraction transform.*

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1. Introduction

Chat Generative Pre-trained Transformer (ChatGPT) is an innovative tool that can answer questions on almost everything in the modern digital world as long as it comes from the dataset on which it was trained [22]. Nowadays, ChatGPT producing responses that are coherent, logical, relevant, and fluid, creating the impression that content on screen is physically typed by someone [7]. To customize educational process for their pupils, the educators can employ ChatGPT in their classes [25]. However, students writing skills can be improved by using text completion, translation and summarizing methods. Features of ChatGPT can utilized to detect bias in content also address issues by instructional materials [21]. With the demand for up-to-date instructional resources increasing, ChatGPT can benefit states develop also execute an unbiased also equitable curriculum [32]. If properly executed, this could serve as a buffer to relieve some of the strain on an overburdened educational system. Teachers can utilize ChatGPT as a helpful tool to improve their role. Also, give them more useful resources to strengthen them. By using ChatGPT to promote conversations, provide personalized feedback, and improve their language and literacy abilities, educators may improve the learning outcomes of their students [31]. Students can get individualized coaching and feedback with ChatGPT. The program can provide a student with detailed feedback on their written work as well as ideas for enhancement and motivation [34]. Pupils may feel self-assured and driven to keep learning and developing. ChatGPT understands issues statement after examining a text, like a phrase or prompt, and generates a response [29]. The model is trained to predict the next word in a phrase based on the context of the words that come before it. Essays can be automatically graded by ChatGPT with logic and even better solutions [19]. This tool allows instructors mark written assignments and remark on their content, language, structure, and plagiarism. Creating concepts, synopses, also even entire speeches can help with speech writing [28]. By helping students find and arrange material for papers and other kinds of study, it might support research [3]. ChatGPT can help language learners by giving them instant feedback on their grammar and pronunciation, which can help them improve their language skills more quickly [26]. It may assist children struggle with writing and reading by offering tips on how to make their sentences and paragraphs better [8, 15, 23]. The ChatGPT language model has the potential to generate writing that is similar to that of a human writer [33]. It can carry out a number of activities related to Natural Language Processing (NLP), such as conversation systems, text production, text summarization, and language translation [4]. A sizable dataset of internet data, including webpage's, books, research articles, social media posts, and talk is used to train it [13]. Referencing cultural, emotional, and physical experiences from training data, remembering prior exchanges within the same conversation when speaking in human [5], also creatively solving problems by utilizing a variety of scientific and technical expertise, ChatGPT generally performs at its best [17].

1.1. Problem Statement and Motivation behind this Research Work

While experiencing for students with different skill levels and learning speeds are delayed by ChatGPT. Furthermore, it cannot be used to confirm and improve the caliber of instructional materials produced by ChatGPT. Creating systems for ChatGPT-based real-time evaluation and feedback production in educational settings is erroneous. Here driven by this issue to create a strong defense against the aforementioned ill-posed region without compromising the accuracy of other regions.

The DSSRAN-CGPT is proposed for increasing the performance of investigation in ChatGPT in education. To classify the sentiment of ChatGPT in education under with positive, negative and neutral sentiment, DSSRAN is utilized. Parrot Optimization Algorithm (POA) is introduced to optimize DSSRAN in order to improve the performance and more effectively detecting and classifying the sentimental analysis in ChatGPT in education.

1.2. Contribution

- In this research work, Investigation of ChatGPT's Impact on education Using Deep Spectral-Spatial Residual Attention Networks (DSSRAN-CGPT) is proposed.
- The Synchro-Transient-Extraction Transform (STET), is set to extract the term statistical features, it penalizes text differences that belong on the same scene plane but don't follow the same model's parameters.
- The first point of novelty also significance is idea of joining DSSRAN it develops in the framework that is demonstrably capable of classifying the Investigation of ChatGPT in education.
- The DSSRAN technique is a significant contribution, because it outperforms other processes with the similar structure also requires less complex DSSRAN layers.

Remaining paper is arranged as below: Section 2 describes literature review; section 3 depicts proposed technique, section 4 exhibits result with discussions, section 5 gives conclusion.

2. Literature Survey

Numerous researches have presented in the literature related to ChatGPT in education using Deep Learning (DL); among them some recent researches are revised here, Rejeb *et al*. [27] have presented exploring the impact of ChatGPT in education: A web mining along Machine Learning (ML) method. Artificial Intelligence (AI) based ChatGPT has attracted more attention in education. The ChatGPT examined public perception of ChatGPT's influence on education using web mining and NLP techniques. The study uses an empirical methodology and ML algorithms to process web articles to obtain significant insights. But also revealed issues with academic integrity related to utilize AI-driven tools like ChatGPT in the, like plagiarism and cheating. It raises ethical questions about responsible AI usage and data protection, among other things. It also emphasizes the necessity for institutions to create rules and norms to utilize AI tools in education. It attains higher accuracy and it attains lower precision.

Javaid *et al*. [12] have presented unlocking the opportunities via ChatGPT towards improving the system of education. Based on AI, the Open AI-developed ChatGPT was widely utilized in industries, including learning. Using this technology to create data, students were able to discover concepts and theories. DL, NLP, ML, an extension of a class of ML-NLP methods called Large Language Models (LLMs) were the foundation of ChatGPT. It can be used to automatically grade tests and assignments, giving teachers more time to concentrate on instructing. It attains higher precision and it attains lower specificity.

Li *et al*. [16] have presented ChatGPT in education: A discourse assessment of worries and concerns on social media. There are new prospects in education sector due to rapid improvements in reproductive AI methods. But it's crucial to identify also deal by any hazards or issues can come up when utilizing them. To determine the main issues surrounding the usage of ChatGPT in education, we examined data from Twitter. In order to perform a discourse examination and social network analysis to determine who the conversation's influential users were, we used BERT-based topic modeling. While most twitter users have favorable things to say about using ChatGPT. It attains higher recall and it attains lower f1score.

Fatouros *et al*. [9] have presented transforming sentiment analysis in the financial field including ChatGPT. When it comes to interpreting market patterns and directing strategic trading choices, financial sentiment analysis is indispensable. This work sets new standards by examining the possibilities of big language datasets, even in the face of the financial industry's use of sophisticated DL methods also language methods to improve sentiment analysis. Models in financial sentiment analysis, which focus on foreign exchange market, especially on ChatGPT 3.5. It attains lower computation time and it attains lower Receiver Operating Characteristic curve (ROC).

Gill *et al*. [10] has presented Transformative effects of ChatGPT in modern learning: Emerging era of AI Chat bots. An AI-powered chatbot called ChatGPT provides thoughtful and helpful responses by analyzing vast amounts of data. Here, eminent scholars, scientists, engineers, and distinguished scholars discuss how ChatGPT is transforming education in modern day. This study discusses ChatGPT's features and apps in educational field, as well as potential problems also difficulties. According to our initial assessment, ChatGPT performs differently when it comes to finance, coding, arithmetic, and general public enquiries, among other topic areas. It attains higher ROC and it attains higher computation time.

Zirar [35] have presented Exploring impact of language methods, like ChatGPT. Debate was spurred by recent advances in language methods, like ChatGPT. These tools can be used by students to create assessed work and can assist, for example, dyslexic individuals in writing formal emails based on prompts. Language models, according to its supporters, improve both academic performance and the student experience. People who were worried contend that language models hinder students' learning and urge caution while implementing them. It attains higher specificity and it attains lower accuracy.

Prajapati *et al*. [24] have presented AI-assisted generative pretrained transformers for apps of ChatGPT in higher learning between graduates. The sector of education focused on sustainable development has expanded, especially in the last several years. A comprehensive educational program now requires measuring degree of technologically oriented educational progress. AI-based technology has been developing steadily and permeating more and more aspects of our lives. Online classes and additional low-storage study resources combined by AI were enabling bit-sized learning in education while keeping a human touch. It attains higher F1-score and it attains lower recall.

Alyasiri *et al*. [2] have presented Exploring GPT-4's characteristics utilizing 5Vs of big data: A brief perspective. It examines GPT-4's integration with big data, highlighting its ability to manage large textual datasets and its expansion into image recognition, enhancing versatility. GPT-4 addresses big data's key aspects: Volume, Variety, and Veracity. It processes vast amounts of data in real-time, evaluates diverse training data for accuracy, and provides actionable insights, making it a valuable tool in AI for handling complex datasets. The paper emphasizes GPT-4's adaptability and scalability in data processing. It attains lower computation time and it attains lower ROC.

3. Proposed Methodology

In this section, DSSRAN-CGPT method is proposed. This procedure consists of 5 steps: Data acquisition, pre-processing, feature extraction, sentiment classification and optimization. The proposed method is used to analyze the sentiment on education in ChatGPT, undergo pre-processing to prepare them for further analysis. Then the features are extracted using ChatGPT sentiment analysis dataset. The final step involves DSSRAN method to classify method classify ChatGPT in education as positive sentiment, negative sentiment and neutral sentiment. The POA method is introduced for optimizing the DSSRAN. The block diagram of the DSSRAN-CGPT approach is portrayed in Figure 1. The detailed description of all the steps is given below,

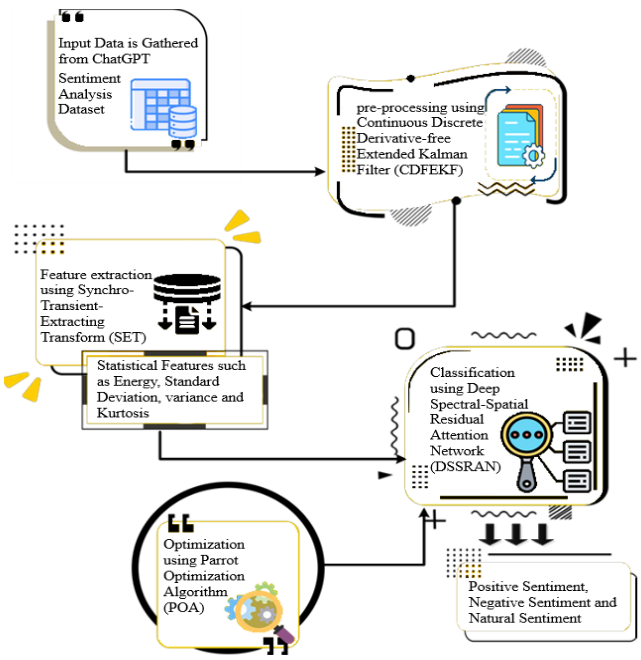

Figure 1. Block diagram for proposed DSSRAN-CGPT method.

3.1. Data Acquisition

Input data is collected via ChatGPT sentiment analysis dataset [11]. The tech community has been talking a lot about ChatGPT. After collecting the ChatGPT tweets for a month, NLP was used to provide a sentiment analysis.

3.2. Pre-Processing Using Continuous-Discrete Derivative-Free Extended Kalman Filter

In this section, CDFEKF Continuous-discrete Derivative-free Extended Kalman Filter (CDFEKF) method [14] is utilized to remove the unwanted data from the collected input data. The typical CMCESKF riddle is given and the effect of external acceleration is investigated. A weighted correntropy is provided to correct for removing the unwanted text data. Next, a compact CMCESKF is made using the CDFEKF metric, and it performs admirably at identifying the unwanted text or sentence data. A CDFEKF evaluating each estimate of the gathered data using Equation (1)

$$\underbrace{\left[\bar{C}_{L|L-1}\, q_l^{1/2}\right]}_{pre-array}\Theta = \underbrace{\left[q_{f,l}^{1/2}\right]}_{postarray} \tag{1}$$

where, $\bar{C}_{L/L-1}$indicates the dynamically updated with each repetition of text data; $q_l^{1/2}$ denotes the corresponding error from the collected input text data; Θ indicates the multiplication fiction of CDFEKF and $q_{fj}^{1/2}$ indicates the Kalman bandwidth for channel between *f* and *l*. In CMCESKF, each text data is flipped to represent the measurement of each sentence covariance matrix using Equation (2).

$$L_l = S_{ac.l}\, q_{f,l}^{-t/2}\, q_{f,l}^{-1/2} \tag{2}$$

where, *Ll* indicates the text-wise plane in each sentence or text data and $S_{ac.l}$ indicates the i^{th} text depth size of each sentimental data. The scalar fading factor is generated using the adjusted measurement of each unwanted text removal covariance matrix and the covariance in pixel matrix generated by the noise exponential weighting technique using Equation (3).

$$\underbrace{\left[\left(\bar{A}_{l|l-1} - L_l \bar{A}_{l|l-1}\right) L_l q_l^{1/2}\right]}_{\Pr e-Array}\Theta = \underbrace{\left[S_{l|l}^{1/2}\ 0\right]}_{Post-array} \tag{3}$$

where, $\bar{A}_{L|L-1}$ indicates the pair of text data in each sentence and $S_{l|l}^{1/2}$ indicates the regularization factor that aids in avoiding the unwanted text in input data. It's a non-linear filter that can filter things down and preserve text data. The CMCESKF weight, which was determined by taking the Euclidean distance of the data, was computed by comparing the similarity between the intermediate and surrounding text data. Similar to this, the CMCESKF approach uses a weighted average of ambient of each text data to represent text intensity using Equation (4).

$$\underbrace{\begin{bmatrix} \bar{A}_{l|l-1} & q_l^{1/2} \\ \bar{A}_{l|l-1} & 0 \end{bmatrix}}_{\Pr e-array}\Theta = \underbrace{\begin{bmatrix} q_{f,l}^{1/2} & 0 \\ \bar{S}_{zc,l} & S_q^{1/2} \end{bmatrix}}_{Post-array} \tag{4}$$

where, $S_q^{1/2}$ is the stage's coefficient determines how much data filtering is applied to each text overall. Unwanted text estimation is last step in preparation procedure because retained text data is mistakenly identified as the sentimental text edge and cannot be determined by usually based on unwanted text estimation. The previously described is made worse by the predicted cleaning level's steep fall, and unwanted text is conducted using Equation (5).

$$\underbrace{\left[\overline{EA}_{l-1|l-1}^{FN,(k)}\ \sqrt{\delta}\, HR^{1/2}\right]}_{\Pr e-array}\Theta = \underbrace{\left[\left(S_{l-1|l-1}^{(l+1)}\right)^{1/2}\right]}_{Post-array} \tag{5}$$

where, $\overline{EA}_{l-1|l-1}^{FN,(k)}$ is the element that, in the event that the unwanted text of each document or sentence is insufficient, stabilizes the text division; $\sqrt{\delta}HR^{1/2}$ indicates the unwanted data obtained from the gathered input data and $S_{l-1|l-1}^{(l+1)}$. By processing CDFEKFmethod removes the unwanted data from the collected input data. Then pre-processed data is supplied towards the feature extraction.

3.3. Feature Extraction under Synchro-Transient- Extraction Transform

The STET [20] is the most suitable choice for feature extraction in this scenario due to its ability to extract essential statistical features like Energy, Standard Deviation, Variance, and Kurtosis, which capture both subtle and prominent patterns in the data. Its robustness against noise ensures effective separation of relevant information from distortions, making it ideal for complex datasets with dynamic variations. STET provides an efficient representation of key information, enhancing the accuracy of downstream tasks such as classification and prediction. This adaptability and noise resilience make STET highly effective for accurate and reliable feature extraction in this context. Only the extracted text that, depending on the source text and each function, is more relevant to the unwanted text is retained by the STET. STET is a larger set of extracted text that allows for quick and accurate image characterization for a variety of text sizes using Equation (6).

$$\hat{z}(T,\omega) = \begin{cases} \partial_T \hat{\omega}(T,\omega) / \partial_T \hat{T}(T,\omega), & if\ \partial_T \hat{T}(T,\omega) \neq 0 \\ Inf & ,if\ \partial_T \hat{T}(T,\omega) = 0 \end{cases} \tag{6}$$

where, $\hat{z}(T,\omega)$ indicates the processed text data; ∂_T represents the phase-aligned linear text data; $\hat{\omega}$ indicates the texts that were extracted longitudinally and $\hat{T}$ represents the total amount of texts present in each sentence. When STET analyses considerably variable no stationary text data, it reassigns the distributions just along the synchro-transient extracting text axis; the total reassignment will decrease. To align with the changing trend, a refined STET estimator has been utilized to provide using Equation (7).

$$t_f(T,\omega) = \begin{cases} U(T,\omega)\partial(\omega - \hat{\omega}(T,\omega)), & if\ |\hat{z}(T,\omega)| > \beta^{-2/3} \\ 0 & ,\ Otherwise \end{cases} \tag{7}$$

where, t_f indicates the ratio of the text from each sentimental documents; *U* indicates each feature's threshold value; and $\beta^{-2/3}$ indicates the longitudinal synchro-transient extracting operator. Any text can be computed by splitting it into categorical or non-categorical, and then computing the texts of the categorical or non-categorical, and using these formulas to generate sentiment text data whose boundaries are then gathered using Equation (8).

$$\left(\hat{T}(T,\omega)-T\right)\partial_T\hat{\omega}(T,\omega)/\partial_T\hat{T}(T,\omega)=z^2\beta^2(\omega-y-zT)\left(1+z^2\beta^2\right)^{-1} \quad (8)$$

where, β^2 indicates the flat surface of the error texts and positive texts and y indicates the text planar regions in the scene. Although this text-by-text method is computationally effective, no single text contains all the data required to detect the transmission. Therefore, improper transmission data leads to overexposed features in texts. However, each text extraction procedure adjusts the multilevel thresholding objective text in order to apply a patch-wise strategy using Equation (9).

$$U\left(T, y+zT\right) = p_e\left(T\right)\sqrt{2\pi\beta\left(1-i\beta z\right)^{-1}} \quad (9)$$

where, $p_e(T)$ Dv demotes the text that are rearranged in sentence and $\sqrt{2\pi\beta(1-i\beta z)^{-1}}$ represents each sentences text-by-text plane properties at a range of text sizes. Energy is used to characterize a data measurement during the execution of an operation inside a probability framework, serving as a (maximum a priori) evaluation in conjunction with the Markov random domain. Depending on the situation, energy can be used as a positive or negative measure to reduce using Equation (10).

$$K=\sum_j\sum_i e(j,i)^2 \quad (10)$$

where, K represented as the energy feature; $e(i,\ j)$ denotes the extracted sentimental data from the processed data. Standard deviation computes mean distance among data value also mean, where a better value denotes a high contrast also a standard deviation value displays that there is less variation of the pixels from the mean using Equation (11).

$$\sigma=\sqrt{\sum_{i=1}^{s}\sum_{j=1}^{s}\frac{\left(e(i,j)-M\right)^2}{sd}} \quad (11)$$

where, σ denotes the standard data; M and sd indicates the standard deviation function. Once the mean value is subtracted, the variance is defined as the signal square mean and it given in Equation (12)

$$V=\tfrac{1}{e}\sum(X_j-M)^2 \quad (12)$$

where, V indicates the variance and X_j $p(i,j)$ is the text's intensity value at position $(i,\ j)$. It gauges the distribution's stability in relation to the normal distribution and it is given as Equation (13).

$$Kurtosis=\sum_{j=1}^{M}\sum_{i=1}^{N}\frac{\left(e(j,i)-m\right)^4}{(MN)\partial^4} \quad (13)$$

where, MN represents the source text and ∂^4 indicates the extracted text features. Finally, the statistical features are extracted. Then these extracted features are fed to DSSRAN to classify the sentimental analysis as positive, negative and neutral.

3.4. Classification Using Deep Spectral-Spatial Residual Attention Network

In this section, DSSRAN method [6] is discussed for classifying investigation of ChatGPT as positive sentiments, negative sentiments and neutral sentiments on education. The investigation on ChatGPT uses a DSSRAN model that victories individual words to analyze text. This model is composed of two layers of DSSRAN. More specifically, it builds a dictionary of terms using the training text input, from which those words' vector representation is learned using Equation (14).

$$S_{avg}=\frac{1}{g\times v}\sum_{i=1}^{g}\sum_{j=1}^{v}E_{i,j} \quad (14)$$

where, S_{avg} indicates the activation functions also a dropout layer to avoid DSSRAN method over fitting; g indicates the total number of channel layers; v indicates the pooling operation and $E_{i,\ j}$ indicates the sentiment value at position (i, j) in DSSRAN, of input E. In order to extend the network and allow text from one layer to be carried over to one before it, skip connections are employed. Since the skip connections along its shortcut path have no extra parameters, they solve the vanishing gradient problem in text by using a back propagation stage for faster training using Equation (15).

$$E_{Skip}=A\otimes C \quad (15)$$

where, E_{Skip} indicates the skip connection between each layer in categorizing each word; A denotes the mapping function in each layer; $\otimes$ indicates the element wise multiplication in identifying the sentiment words from data and C indicates the non-linear representation while extracting the mapped function. To improve the retrieved spectral features, two bottleneck fully connected layers are taken into consideration. This layer typically supports the ability of the model to be generalized while reducing model complexity using Equation (16).

$$E_{YN-\mathrm{Re}LU}=\delta\left(E_{YN}\right) \quad (16)$$

where, $E_{YN\text{-}\mathrm{Re}LU}$ indicates the bottleneck fully linked layers are taken into consideration to improve the classification that are retrieved and $\delta(E_{YN})$ is a layer that reduces dimensionality. Because there isn't a parameter in the global average pooling to optimize, overfitting is prevented at this layer. After being flattened, the output is fed into a fully connected layer for probability distribution and sentiment classification, together with a softmax function using Equation (17).

$$E_{output} = Sof\left(E_{SHEZ}\right) \quad (17)$$

where, E_{output} is the second layer is a layer that increases dimensionality; *Sof* indicates the softmax function and E_{SHEZ} symbolizes the fully connected operation, dropout, and pooling, respectively. The DSSRAN is primarily concerned with limiting texts with differing class labels and enhancing spatial data for surrounding input texts that have the same class label as the sentimental texts. Therefore, a matrix with similar height also width as input text, where value of a numerical text at this place by same label as centre equals 1 or else 0, then sentiment is classified as the output of positive, negative and neutral using Equation (18).

$$Loss_{ZF} = -\frac{1}{n}\sum_{N=1}^{n}\sum_{z=1}^{Z} b_z^N \log\left(\hat{b}_z^N\right) \quad (18)$$

where, $Loss_{ZF}$ indicates the loss function of DSSRAN; b_z^N represents the classified sentimental data; log indicates the logarithm function between identifying the sentiments and $\hat{b}_z^N$ indicates the actual and predicted labels respectively. Finally, DSSRAN classified investigation of ChatGPT in education such as positive negative and neutral sentiments. The DSSRAN classifier incorporates an AI-based optimization strategy due to its practicality and relevance. Here, POA method is applied to optimize the DSSRAN. POA is applied for tuning weight and bias factor of DSSRAN.

3.5. Optimization Using Parrot Optimization Algorithm

A proposed POA method [32] is utilized to enhance weights parameters $E_{i\,j} and \hat{b}_z^N$ of proposed DSSRAN. The parameter Ei,j is implemented for increasing the accuracy and $\hat{b}_z^N$ lessing the computation time. The Pyrrhura Molinae is a popular species of parrot that is preferred by pet owners because of its endearing appearance, strong attachment with their owners, and ease of training. Four different behavioral features have been identified in Pyrrhura Molinae by previous investigations and breeding efforts: foraging, remaining, communication, and fear of strangers. The POA was designed with these behaviors in mind, based on examples from real-world situations. Interesting facts about foraging habits of domesticated Pyrrhura Molinae include their preference to forage in small groups when there is an abundance of food. By using the group's presence and their owner's position, they can find the meal by moving in its direction. They use scent and visual cues to refine their search. The stepwise procedure for acquiring proper DSSRAN values utilizing POA is labelled here. To creates evenly distributed population for optimizing the ideal DSSRAN parameters. The entire stepwise method is presented below;

- *Step* 1: Initialization

Initial populace of POA is initially created randomwise. This is expressed in Equation (19).

$$A_i^0 = Ly + Rand\left(0,1\right).\left(Uy - Ly\right) \quad (19)$$

where, A_i^0 indicates where the i^{th} Pyrrhura Molinae is in the first stage; Ly indicates the search space limits of lower bound; *Rand* indicates the random amount in range [0,1] also Uy indicates the search space limits of upper bound.

- *Step* 2: Random generation

The input weight parameter $E_{i,j}$and$\hat{b}_z^N$ developed randomness via POA.

- *Step* 3: Fitness function

It creates random solution from initialization. It is computed by optimizing parameter using Equation (20).

$$Fitness\ Function = optimizing\ [E_{i,j} and \hat{b}_z^N] \quad (20)$$

where $E_{i,j}$ is implemented for increasing the accuracy and $\hat{b}_z^N$ is used to lessing the mean square error.

- *Step* 4: Foraging behavior for optimizing $E_{i,j}$

They often use observation to find out the location of food during foraging behavior in PO, or they considered the owner's position. Then, they fly in the direction of the estimated location of food using Equation (21).

$$A_i^{T+1} = \left(A_i^T - A_{Best}\right).levy\left(\dim\right)E_{i,j} + Rand\left(0,1\right).\left(1 - \frac{T}{Max_{iter}}\right)^{\frac{2}{Max_{iter}}}.A_{Mean}^T \quad (21)$$

where, A_i^{T+1} indicates where the i^{th} Pyrrhura Molinae is in the first stage; A_i^T indicates the current location of POA; A_{Best} symbolizes average position at the current population; $(1 - \frac{T}{Max_{iter}})^{\frac{2}{Max_{iter}}}.A_{Mean}^T$ indicates surveillance of the populace's overall positioning to further target the orientation of food; $E_{i,j}$ indicates the sentiment value at position (i, j) in DSSRAN, of input E and $levy$(dim) shows motion according to one's position in reference to owner. The remarkable thing about domesticated Pyrrhura Molinae's foraging behavior is that they prefer to gather food in pairs when food is plentiful. By using the group's presence and their owner's position, they can find the meal by moving in its direction. They improve their search with visual and olfactory cues using Equation (22).

$$A_{Mean}^T = \frac{1}{N}\sum\nolimits_{L=1}^{N} A_L^T \quad (22)$$

where, A_{Mean}^T indicates average positioning of the current POA, A_L^T indicates the foraging behavior of POA and N indicates the n^{th} number of POA.

- *Step* 5: Staying behavior for optimizing $\hat{b}_z^N$

An abrupt flight to any region of its possessor's body is the major staying behavior of the highly gregarious Pyrrhura Molinae, which remains stationary for a predetermined period of time using Equation (23).

$$A_i^{T+1} = A_i^T + A_{Best}.levy(Dim)\times \hat{b}_z^N + Rand(0.1).ones(1, Dim) \quad (23)$$

here, $ones(1, Dim)$ indicates act of stopping at random location on host's body and $\hat{b}_z^N$ represents the classified sentimental data.

- *Step* 6: Communicating behavior

Parrots, which belong to the Pyrrhura Molinae family, are naturally gregarious and communicate closely with one another in groups. Both flying to join the flock and conversing without taking off for it were examples of this communication activity. The mean position of the current population represents the center of the flock, and both behaviors are assumed to occur equally frequently in the POA using Equation (24).

$$A_i^{T+1} = \begin{cases} 0.2.Rand(0,1).\left(1-\frac{T}{Max_{iter}}\right).\left(A_i^T - A_{Mean}^T\right), & S \le 0.5 \\ 0.2.Rand(0,1).Exp\left(-\frac{T}{Rand(0,1.Max_{iter})}\right), & S > 0.5 \end{cases} \quad (24)$$

where, $Exp\left(-\frac{T}{Rand(0,1.Max_{iter})}\right)$ indicates that someone takes off right after they have a conversation and S signifies the act of a person communicating with a parrot by joining its group.

- *Step* 7: Fear of stranger's behavior

Birds in general and Pyrrhura Molinae parrots in particular, have an innate fear of strangers. Their propensity to avoid unfamiliar situations and seek solace with their owners in an attempt to find a safe haven and it is given in Equation (25).

$$A_i^{T+1} = A_i^T + Rand(0,1).Cos\left(0.5\pi.\frac{T}{Max_{iter}}\right).\left(A_{Best} - A_i^T\right) - Cos(Rand(0,1).\pi).\left(\frac{T}{Max_{iter}}\right)^{\frac{2}{Mac_{iter}}}.\left(A_i^T - A_{Best}\right) \quad (25)$$

where, Cos indicates the act of turning around to fly in the direction of its owner and retreating from outsiders. Figure 2 shows that,

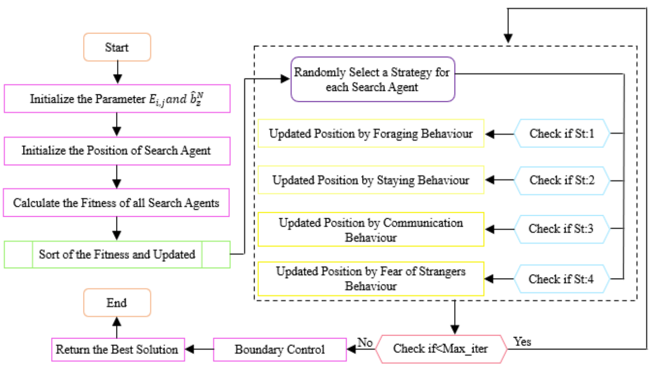

Figure 2. Flow chart of POA for optimizing DSSRAN.

- *Step* 8: Termination

A weight parameter value of producer $E_{i,j}$ *and* $\hat{b}_z^N$ via attention-based DSSRAN method is enhanced by POA; otherwise, it will repeat step 3 until it obtains its halting condition $A_i^0 = A_i^0 + 1$. DSSRAN-CGPT assesses the quality of ChatGPT in education accurately by lessening computation time with error.

4. Result and Discussion

This section deliberates about the experimental outcomes of the proposed method [30]. The simulation is coded with in PYTHON utilizing ChatGPT sentiment analysis dataset. The DSSRAN model is tested against several performance metrics. The attained result of DSSRAN-CGPT method is compared with existing techniques, like CGPT-ELA [27], CGPT-AES [12] and CGPT-WCSM [16].

4.1. Performance Measures

The following metrics is examined to confirm the robustness of the proposed method.

4.1.1. Accuracy

Accuracy describes detection rate that are correctly analyze investigation of ChatGPT in education. This is determined by Equation (26).

$$Accuracy = \frac{(TP+TN)}{(TP+FP+TN+FN)} \quad (25)$$

Consider TP as True Positive; TN as True Negative; FP as False Positive, FN as False Negative.

4.1.2. Precision

It estimates positive result count while analyze the investigation of ChatGPT in education. This is computed by Equation (27).

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

4.1.3. F1-Score

The evaluation parameter of $F1$-*score* is analyzed by Equation (28).

$$F1-Score = 2\times\frac{recall\times precision}{recall + precision} \quad (28)$$

4.1.4. Recall

Recall is a performance metric commonly used in binary classification tasks, based on reviews, where the goal is to correctly identify the negative sentiment analysis. This is calculated by Equation (29).

$$\text{Recall} = \frac{TN}{(FP+TN)} \quad (29)$$

4.1.5. Specificity

This is the rate of negative instances and is calculated by Equation (30).

$$Specificity = \frac{TP}{FN + TP} \quad (30)$$

4.1.6. ROC

ROC is defined as the ratio of *FN* to *TP* areas by using Equation (31).

$$ROC = 0.5 \times \left(\frac{TP}{TP+FN} + \frac{TN}{TN+TP} \right) \quad (31)$$

4.1.7. Computation Time

The term "computation time" describes how long a computer or algorithm needs to run a certain operation, computation, or activity. Dependent on size also complexity of mission, it is a crucial indicator of performance and efficiency in computing systems and is frequently stated in seconds, milliseconds, microseconds, or nanoseconds.

4.2. Performance Analysis

Figures 3 to 9 show simulation result of DSSRAN-CGPT method. The performance metrics are analyzed with existing CGPT-ELA, CGPT-AES and CGPT-WCSM methods.

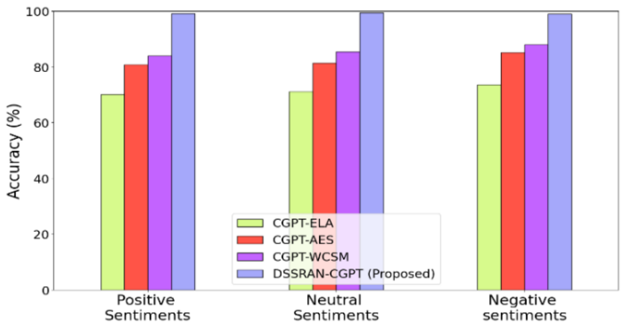

Figure 3. Performance analysis of accuracy.

Figure 3 indicates the accuracy analysis. The graph provides the classification accuracy of various models for the positive, neutral, and negative attitudes associated with ChatGPT's influence on education is compared. Below is an analysis of the graph: Axis vertical Y-axis displays accuracy as a percentage between 0 and 100. Axis Horizontal X-axis separated into three groups of feelings: neutral, negative, and positive. The accuracy of each model in identifying feelings is displayed on the graph. It seems that the DSSRAN-CGPT Proposed model performs the best in all sentiment categories as, 18.21%, 22.96% and 30.77% higher accuracy for positive sentiments; 15.44%, 24.90% and 31.30% higher accuracy for neutral sentiments and 18.64%, 26.12% and 34.49% higher accuracy for negative sentiments which is analyzed with existing CGPT-ELA, CGPT-AES and CGPT-WCSM methods individually.

Figure 4 indicates precision. A graph displays the precision for neutral, negative, and positive feelings for each model. Across all sentiment categorized as positive, neutral and negative, the proposed model DSSARN-CGPT achieves the greatest precision rates. Nearing precision, CGPT-WCSM demonstrates strong performance, particularly in neutral and negative attitudes. Though it still does rather well in neutral moods, CGPT-ELA typically has the lowest precision of all the models. When it comes to both positive and negative attitudes, CGPT-AES (highlighted in red) outperforms CGPT-ELA, although CGPT-WCSM and DSSARN-CGPT do better. It seems that the DSSRAN-CGPT Proposed model performs the best in all sentiment categories as, 16.43%, 24.29% and 30.82% higher precision for positive sentiments; 15.09%, 23.41% and 31.86% higher precision for neutral sentiments and 17.05%, 24.43% and 35.89% higher precision for negative sentiments which is analyzed with existing CGPT-ELA, CGPT-AES and CGPT-WCSM methods respectively.

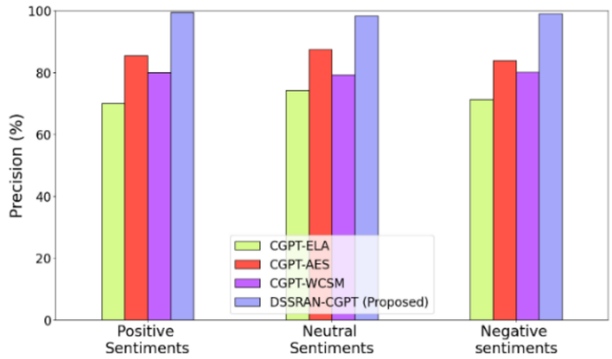

Figure 4. Performance analysis of precision.

Figure 5 indicates the specificity. The given graph contrasts the specificity of many techniques for classifying sentiments into positive, neutral, and negative categories. Three sorts of sentiments are displayed on the x-axis: negative, neutral, and positive sentiments. Specificity is plotted as a percentage on the y-axis, with values ranging from 0% to 100%. Specificity is a measure of how well a method detects TNs, or occurrences of non-target classes, and is given as a percentage. The method's ability to prevent FPs improves with increasing specificity. All emotion categories positive, neutral, and negative exhibit the maximum specificity when using the proposed approach, DSSRAN-CGPT. This approach is the most dependable since it shows the highest efficacy in correctly identifying various sentiment categories with the fewest FPs. It appears that DSSRAN-CGPT is especially skilled at handling these more difficult emotion classifications, as evidenced by the notable gain in specificity for neutral and negative attitudes. It seems that the DSSRAN-CGPT Proposed model performs the best in all sentiment categories as, 26.89%, 29.49% and 18.64% higher specificity for positive sentiments; 35.60%, 30.41% and 18.75% higher specificity for neutral sentiments and 26.80%, 14.41% and 26.60% higher specificity for negative sentiments which is analyzed with existing CGPT-ELA, CGPT-AES and CGPT-WCSM methods respectively.

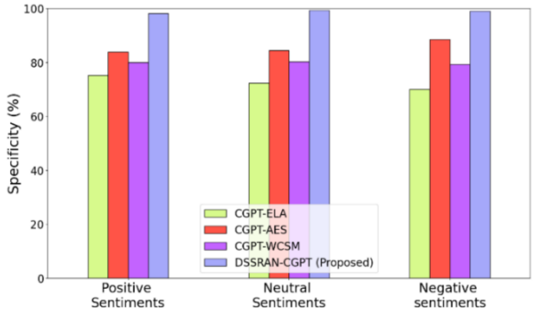

Figure 5. Performance analysis of specificity.

Figure 6 indicates the recall. The recall percentage, which gauges the model's accuracy in locating pertinent examples of each sentiment type, is represented by the vertical Y-axis. The range of the scale is 0% to 100%. Three categories as positive, neutral and negative represent the various sentiment kinds that are represented by the horizontal x-axis. All sentiment types consistently yield the highest recall percentages, with the DSSRAN-CGPT Proposed model hitting 99.7 % in every instance. In all sentiment kinds, CGPT-WCSM outperforms CGPT-ELA and CGPT-AES, but it falls short of the proposed model. It also demonstrates how the other models outperform them despite their moderate performance. It indicates that the DSSRAN-CGPT Proposed model performs the best in all sentiment categories as, 16.60%, 20.06% and 25.35% higher recall for positive sentiments; 32.62%, 30.60% and 17.85% higher recall for neutral sentiments and 22.32%, 21.52% and 30.21% higher recall for negative sentiments which is analyzed with existing CGPT-ELA, CGPT-AES and CGPT-WCSM methods respectively.

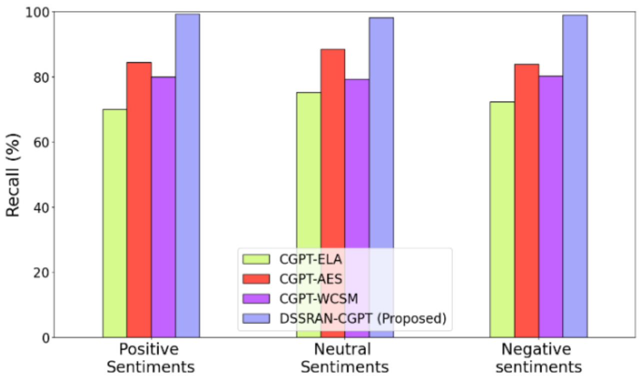

Figure 6. Performance analysis of recall.

Figure 7 indicates the F1-score. F1-score as the assessment metric, the graph compares the performance of three sentiment analysis models for each of the three sentiment categories as Positive, Neutral, and Negative. F1-score is a trial accuracy metric that takes precision also recall into account while calculating the result. It is particularly helpful in cases of unequal class distribution. In every sentiment category, the proposed DSSRAN-CGPT model performs better than the other three models CGPT-ELA, CGPT-AES, and CGPT-WCSM. Compared to the other models, the DSSRAN-CGPT model exhibits much higher F1-scores in every category, indicating its superior efficacy in sentiment analysis. The F1-score discrepancy between DSSRAN-CGPT and the other models is significant, particularly in the neutral sentiment category, where it performs significantly better than the second-best model (CGPT-WCSM). It indicates that the DSSRAN-CGPT Proposed model performs the best in all sentiment categories as, 15.60%, 32.42% and 26.21% higher F1-score for positive sentiments; 30.20%, 16.51% and 30.90% higher F1-score for neutral sentiments and 22.60%, 20.96% and 15.39% higher F1-score for negative sentiments which is analyzed with existing CGPT-ELA, CGPT-AES and CGPT-WCSM methods respectively.

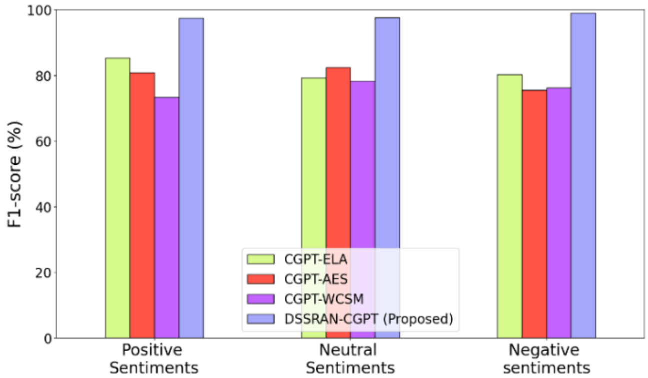

Figure 7. Performance analysis of F1-score.

Figure 8 indicates the computation time. The graph you provide contrasts the calculation times of several techniques employed in a ChatGPT study on DL in education. The DSSRAN-CGPT Proposed approach is the most efficient of the methods compared since it has the lowest computing time. The longer computation periods for CGPT-ELA and CGPT-AES indicate that they are less effective. This graph demonstrates the proposed DSSRAN-CGPT method's computational efficiency, which may make it a superior option for applications in educational settings where speedy processing is essential. It indicates that the DSSRAN-CGPT Proposed model green performs the best in all sentiment categories as, 32.22%, 32.60% and 27.05%lower computation time for Positive, Neutral and negative sentiments which is analyzed with existing CGPT-ELA, CGPT-AES and CGPT-WCSM methods respectively.

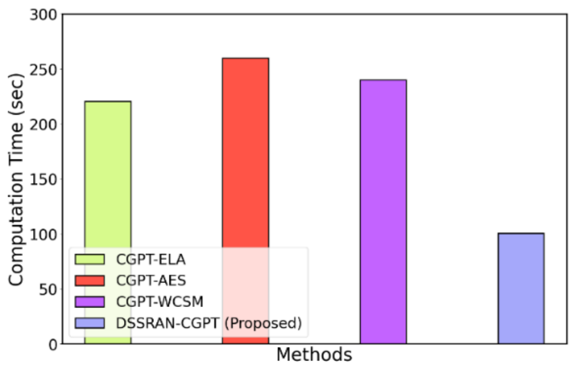

Figure 8. Performance analysis of computation time.

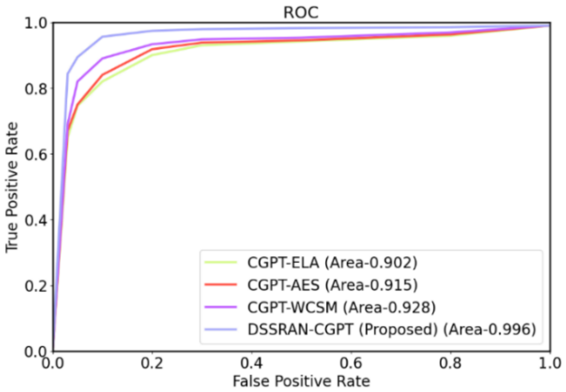

Figure 9. Performance analysis of ROC.

Figure 9 indicates the ROC. The methods capacity to discriminate among classes is indicated by ROC value. The model performs better the closer its ROC value is near 1. With the greatest ROC in this graph, DSSRAN-CGPT performs the best out of all the models that were compared. A percentage of real positives properly detected shown on y-axis. A percentage of real negatives that are wrongly interpreted as positives is shown on x-axis. It indicates that the DSSRAN-CGPT Proposed model green performs the best in all sentiment categories as, 0.90%, 0.91% and 0.92% lower computation time for positive, neutral and negative sentiments which is analyzed with existing CGPT-ELA, CGPT-AES and CGPT-WCSM methods respectively.

4.3. Ablation Study

Table 1 shows the ablation study highlights the significance of each component in the proposed system. The full model (CDFEKF+STET+DSSRAN+POA) achieves the best performance with 99.8% accuracy and a ROC AUC of 0.985. Removing CDFEKF or STET significantly reduces performance, showing their importance in data preprocessing and feature extraction. Replacing DSSRAN with a basic CNN leads to the largest performance drop, emphasizing its critical role in classification. Without POA, the model performs well but shows improved accuracy and optimization when POA is included, validating its contribution to parameter fine-tuning.

Table 1. Ablation study table of the proposed system.

Configuration	Accuracy (%)	Precision (%)	Recall (%)	Specificity (%)	F1-score (%)	Computation time (s)	ROC (AUC)
Full model (CDFEKF+STET+DSSRAN+POA)	99.8	98.5	97.9	98.2	97.7	1.8	0.985
Without CDFEKF (raw input data)	91.3	90.8	91.0	91.5	90.9	2.4	0.918
Without STET (no feature extraction)	89.7	88.9	89.5	90.2	89.2	2.6	0.902
Without DSSRAN (using basic CNN)	88.2	87.8	88.0	88.5	87.9	2.1	0.891
Without POA (unoptimized DSSRAN)	93.5	93.0	93.3	93.7	93.1	2.0	0.936

4.4. Discussion

A novel DSSRAN-CGPT model is proposed in this paper. DSSRAN-CGPT method involves encompasses CDFEKF based pre-processing; STET based feature extraction and DSSRAN based investigation of ChatGPT in education classification as positive sentiment, neutral sentiment and negative sentiment. Finally, DSSRAN model utilized for performing classification process which classify the investigation of ChatGPT in education. The instance of ChatGPT sentiment analysis dataset, average highest results of method were compared to the average results of the existing methods. The proposed methodology for preliminary data development involves classifying data from the ChatGPT sentiment analysis dataset for ChatGPT's education investigation. But the proposed approach uses the POA algorithm in combination with a faster DSSRAN, which makes dataset more effective also addresses issue of over fitting of model more effectively. The accuracy values of DSSRAN-CGPT are 18.21%, 22.96% and 30.77% respectively higher than existing methods like CGPT-ELA, CGPT-AES and CGPT-WCSM respectively. Similar to this, the accuracy of proposed method is 97.57% analyzed with accuracy and precision of comparison techniques of 88.75%. The proposed DSSRAN-CGPT has higher accuracy. The comparative methods are expensive than the proposed method. The proposed method predicts the early investigation of ChatGPT in education more effectively.

5. Conclusions

In this section, DSSRAN-CGPT was successfully implemented. The proposed DSSRAN-CGPT method was simulated in Python utilizing ChatGPT sentiment analysis dataset. By conducting a number of tests to categories the posts and comments the investigation of ChatGPT in education. Then the data are taken from ChatGPT sentiment analysis dataset for classifying the ChatGPT in education as positive sentiment, neutral sentiment and negative sentiment. According to the experimental results, DSSRAN-CGPT performed better in terms of Recall, Specificity, F1-score and ROC. The performance of DSSRAN-CGPT approach attains 16.60%, 20.06% and 25.35% higher recall; 26.89%, 29.49% and 18.64% higher specificity and 15.60%, 32.42% and 26.21% higher F1-score when analyzed with existing methods, like CGPT-ELA, CGPT-AES and CGPT-WCSM respectively. Future work could focus on enhancing model robustness through data augmentation, exploring transformer-based architectures, and expanding the dataset to include diverse educational domains and multilingual data. Incorporating explainability techniques and applying real-time sentiment analysis in personalized learning systems would also be valuable directions for future research.

References

[1] Al Shloul T., Mazhar T., Iqbal M., Yaseen Ghadi Y., Malik F., and Hamam H., "Role of Activity-Based Learning and ChatGPT on Students' Performance in Education," *Computers and Education: Artificial Intelligence*, vol. 6, pp. 100219 2024. https://doi.org/10.1016/j.caeai.2024.10021

[2] Alyasiri O., Akhtom D., and Ali A., "Exploring GPT-4's Characteristics Through the 5Vs of Big Data: A Brief Perspective," *Babylonian Journal of Artificial Intelligence*, vol. 2023, pp. 5-9, 2023. DOI:10.58496/BJAI/2023/002

[3] Amin M., Mao R., Cambria E., and Schuller B., "A Wide Evaluation of ChatGPT on Affective Computing Tasks," *IEEE Transactions on Affective Computing*, vol. 15, no. 4, pp. 2204-2212, 2024. DOI: 10.1109/TAFFC.2024.3419593

[4] Borger J., Ng A., Anderton H., Ashdown G., Auld M., Blewitt M., and Naik S., "Artificial Intelligence Takes Center Stage: Exploring the Capabilities and Implications of ChatGPT and other AI-Assisted Technologies in Scientific Research and Education," *Immunology and Cell Biology*, vol. 101, no. 10, pp. 923-935, 2023. https://doi.org/10.1111/imcb.12689

[5] Chatterjee S., Bhattacharya M., Pal S., Lee S., and Chakraborty C., "ChatGPT and Large Language Models in Orthopedics: From Education and Surgery to Research," *Journal of Experimental Orthopaedics*, vol. 10, pp. 1-10, 2023. DOI:10.1186/s40634-023-00700-1

[6] Chhapariya K., Buddhiraju K., and Kumar A., "A Deep Spectral-Spatial Residual Attention Network for Hyperspectral Image Classification," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing Image Processing*, vol. 17, pp. 15393-15406, 2024. DOI:10.1109/JSTARS.2024.3355071

[7] Farhi F., Jeljeli R., Aburezeq I., Dweikat F., Al-shami S., and Slamene R., "Analyzing the Students' Views, Concerns, and Perceived Ethics about Chat GPT Usage," *Computers and Education: Artificial Intelligence*, vol. 5, pp. 100180, 2023. https://doi.org/10.1016/j.caeai.2023.100180

[8] Farrokhnia M., Banihashem S., Noroozi O., and Wals A., "A SWOT Analysis of ChatGPT: Implications for Educational Practice and Research," *Innovations in Education and Teaching International*, vol. 61, no. 3, pp. 460-474, 2024. https://doi.org/10.1080/14703297.2023.2195846

[9] Fatouros G., Soldatos J., Kouroumali K., Makridis G., and Kyriazis D., "Transforming sentiment Analysis in the Financial Domain with ChatGPT," *Machine Learning with Applications*, vol. 14, pp. 100508, 2023. https://doi.org/10.1016/j.mlwa.2023.100508

[10] Gill S., Xu M., Patros P., Wu H., Kaur R., Kaur K., and et al., "Transformative Effects of ChatGPT on Modern Education: Emerging Era of AI Chatbots," *Internet of Things and Cyber-Physical Systems*, vol. 4, pp. 19-23, 2024. https://doi.org/10.1016/j.iotcps.2023.06.002

[11] https://www.kaggle.com/datasets/charunisa/chatgpt-sentiment-analysis

[12] Javaid M., Haleem A., Singh R., Khan S., and Khan I., "Unlocking the Opportunities through Chatgpt Tool Improving the Education System," *BenchCouncil Transactions on Benchmarks, Standards and Evaluations*, vol. 3, no. 2, pp. 100115, 2023. https://doi.org/10.1016/j.tbench.2023.100115

[13] Jeon J. and Lee S., "Large Language Models in Education: A Focus on the Complementary Relationship between Human Teachers and ChatGPT," *Education and Information Technologies*, vol. 28, pp. 15873-15892, 2023. DOI: 10.1007/s10639-023-11834-1

[14] Kulikova, M. and Kulikov G., "Continuous-Discrete Derivative-Free Extended Kalman Filter Based on Euler–Maruyama and Itô–Taylor Discretizations: Conventional and Square-Root Implementations," *European Journal of Control*, vol. 76, pp. 100960, 2024. https://doi.org/10.1016/j.ejcon.2024.100960

[15] Latif E. and Zhai X., "Fine-Tuning ChatGPT for Automatic Scoring," *Computers and Education: Artificial Intelligence*, vol. 6, pp. 100210, 2024. https://doi.org/10.1016/j.caeai.2024.100210

[16] Li L., Ma Z., Fan L., Lee S., Yu H., and Hemphill L., "ChatGPT in Education: A Discourse Analysis of Worries and Concerns on Social Media," *Education and Information Technologies*, vol. arXiv:2305.02201v1, pp. 1-34, 2023. DOI:10.48550/arXiv.2305.02201

[17] Li Y. and Zhang H., "EEG Signal Recognition of VR Education Game Players Based on Hybrid Improved Wavelet Threshold and LSTM," *The International Arab Journal of Information Technology*, vol. 22, no. 1, pp. 170-181, 2025. https://doi.org/10.34028/iajit/22/1/13

[18] Lian J., Hui, G., Ma L., Zhu T., Wu X., Heidari A., Chen Y., and Chen H., "Parrot Optimizer Algorithm and Applications to Medical Problems," *Computers in Biology and Medicine*, vol. 172, pp. 108064, 2024. https://doi.org/10.1016/j.compbiomed.2024.108064

[19] Lian Y., Tang H., Xiang M., and Dong X., "Public Attitudes and Sentiments toward ChatGPT in China: A Text Mining Analysis Based on Social Media," *Technology in Society*, vol. 76, pp. 102442, 2024.

https://doi.org/10.1016/j.techsoc.2023.102442

[20] Ma Y., Yu G., Lin T., and Jiang Q., "Synchro-Transient-Extraction Transform for the Analysis of Signals with both Harmonic and Impulsive Components," *IEEE Transactions on Industrial Electronics*, vol. 71, no. 10, pp. 13020-130302, 2024. DOI:10.1109/TIE.2023.3344829

[21] Mhlanga D., *FinTech and Artificial Intelligence for Sustainable Development*, Springer Nature Switzerland, 2023.

[22] Nam B. and Bai Q., "ChatGPT and its ethical Implications for STEM Research and Higher Education: A Media Discourse Analysis," *International Journal of STEM Education*, vol. 10, no. 66, pp. 1-24, 2023. DOI:10.1186/s40594-023-00452-5

[23] Parker L., Carter C., Karakas A., Loper A., and Sokkar A., "Graduate Instructors Navigating the AI Frontier: The Role of ChatGPT in Higher Education," *Computers and Education Open*, vol. 6, pp. 100166, 2024. https://doi.org/10.1016/j.caeo.2024.100166

[24] Prajapati J., Kumar A., Singh S., Prajapati B., Thakar Y., Tambe P., and Ved A., "Artificial Intelligence-Assisted Generative Pretrained Transformers for Applications of ChatGPT in Higher Education Among Graduates," *SN Social Sciences*, vol. 4, no. 2, pp. 19, 2024. https://link.springer.com/article/10.1007/s43545-023-00818-0

[25] Praveen S. and Vijaya S., "Examining Otolaryngologists' Attitudes Towards Large Language Models (LLMs) such as ChatGPT: A Comprehensive Deep Learning Analysis," *European Archives of Oto-Rhino-Laryngology*, vol. 281, pp.1061-1063, 2024. https://link.springer.com/article/10.1007/s00405-023-08325-x

[26] Rawas S., "ChatGPT: Empowering Lifelong Learning in the Digital Age of Higher Education," *Education and Information Technologies*, vol. 29, pp. 6895-6908, 2024. https://link.springer.com/article/10.1007/s10639-023-12114-8

[27] Rejeb A., Rejeb, K., Appolloni A., Treiblmaier H., and Iranmanesh M., "Exploring the Impact of ChatGPT in Education: A Web Mining and Machine Learning Approach," *The International Journal of Management Education*, vol. 22, no. 1, pp. 100932, 2024. https://doi.org/10.1016/j.ijme.2024.100932

[28] Saif N., Khan S., Shaheen I., ALotaibi F., Alnfiai M., and Arif M., "Chat-GPT; Validating Technology Acceptance Model (TAM) in Education Sector Via Ubiquitous Learning Mechanism," *Computers in Human Behavior*, vol. 154, pp. 108097, 2024. https://doi.org/10.1016/j.chb.2023.108097

[29] Santhi T. and Srinivasan K., "Chat-GPT Based Learning Platform for Creation of Different Attack Model Signatures and Development of Defense Algorithm for Cyberattack Detection," *IEEE Transactions on Learning Technologies*, vol. 17, pp. 1829-1842, 2024. DOI:10.1109/TLT.2024.3417252

[30] Sun K. and Xu J., "Channel Estimation Algorithm Based on Parrot Optimizer in 5G Communication Systems," *Electronics*, vol. 13, no. 17, pp. 3522, 2024. https://doi.org/10.3390/electronics13173522

[31] Wang C., Li X., Liang Z., Sheng Y., Zhao Q., and Chen S., "The Roles of Social Perception and AI Anxiety in Individuals' Attitudes Toward ChatGPT in Education," *International Journal of Human-Computer Interaction*, pp. 1-18, 2024. https://doi.org/10.1080/10447318.2024.2365453

[32] Yan D., "Impact of ChatGPT on learners in a L2 Writing Practicum: An Exploratory Investigation," *Education and Information Technologies*, vol. 28, no. 11, pp. 13943-13967, 2023. https://link.springer.com/article/10.1007/s10639-023-11742-4

[33] Yilmaz R. and Yilmaz F., "Augmented Intelligence in Programming Learning: Examining Student Views on the Use of ChatGPT for Programming Learning," *Computers in Human Behavior: Artificial Humans*, vol. 1, no. 2, pp. 100005, 2023. http://hdl.handle.net/11772/16182

[34] Zhou J., Liang Z., Fang Y., and Zhou Z., "Exploring Public Response to ChatGPT with Sentiment Analysis and Knowledge Mapping," *IEEE Access*, vol. 12, pp. 50504-50516, 2024. https://ieeexplore.ieee.org/document/10494726

[35] Zirar A., "Exploring the Impact of Language Models, Such as ChatGPT, on Student Learning and Assessment," *Review of Education*, vol. 11, no. 3, pp. e3433, 2023. https://doi.org/10.1002/rev3.3433

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