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Massive Open Online Course (MOOCs) English Courses Based On Hamiltonian Deep Neural Network

JES

Journal of Electrical Systems

Abstract: - Numerous researchers are now concentrating on the English course on intercultural communication. Notwithstanding, these courses encounter several obstacles, including student variations in traditional English for cross-cultural instruction, developing students' cross-cultural communication skills, and improving the quality of instruction. To overcome these problems, in this manuscript, a Hamiltonian deep neural network (NN) approach is proposed for improving the teaching quality of massive open online course (MOOCs) based English course. Initially, data is given from English-language massive open online courses (MOOCs) teaching adult basic life support (ABLS) dataset. Afterward the data is fed to Switching Hierarchical Gaussian Filter. The pre-processing output is provided to the Hamiltonian Deep Neural Network (HDNN) used to improve the teaching quality of MOOC English course. The learnable of the optimized is using Coati Optimization Algorithm (COA). The proposed technique is executed in Python and the effectiveness of the proposed MOOCEC-HDNN method is improved by using various performances evaluating metrics like, teaching Efficiency, Robustness Gain, teaching quality and system Efficiency are analysed. The proposed MOOCEC-HDNN method is shows the higher teaching efficiency of 78%, Robustness Gain of 28dB and teaching quality 68% while comparing other existing methods such as massive open online course (MOOCs) based English course based on Gannet algorithm and Neural Network (MOOCEC-GA-NN), MOOCs based English course based on K-modes algorithm and Neural Network (MOOCEC-KMA-NN) and MOOCs based English course based on Conventional Neural Network (MOOCEC-CNN), respectively.

Keywords: Teaching, English, Massive Open Online Course (MOOCs), Hamiltonian Deep Neural Network (HDNN), Switching Hierarchical Gaussian Filter (SHGF), Students.

I. INTRODUCTION

Recently, scholars globally have dedicated their efforts to exploring the theory of cross-cultural communication ability, particularly within the context of English education [1, 2]. The significance of English intercultural courses has become increasingly apparent, aiming to equip learners with a profound understanding of English culture. The goal is to enable them to critically analyze the distinctions and similarities amid the foreign and native cultures [3]. The key objective of fostering English communication-competency is to cultivate higher quality skills, allowing individuals to communicate successfully with people from diverse backgrounds while instilling a sense of cultural confidence [4, 5]. However, despite the growing demand for such skills in our socially interconnected world, challenges persist within the teaching approaches of English intercultural communication programs at universities and colleges [6]. This has led to the exploration of innovative teaching methodologies that leverage advancements in technology and web-based platforms [7].

The emergence of new technologies and web applications has permeated various facets of our daily lives, presenting opportunities for enhancing educational practices [8].One notable advancement is the utilization of web-based interactive education, which integrates system resources and conventional teaching methods [9]. The advent of the web 2.0 ages has particularly highlighted the advantages of web-related cooperative learning, emphasizing its role in improving learning methods, fostering co-operation between students, and nurturing novelty skills [10]. This study addresses the evolving landscape of English teaching by proposing an innovative method that capitalizes on the collaborative features of the Google platform and Massive Open Online Course (MOOC) platforms [11]. By amalgamating web-related cooperative learning with traditional face-to-face teaching, this approach aims to revolutionize the existing teaching paradigm, offering a more engaging and effective learning environment [12]. The integration of Google's powerful suite of tools and the expansive reach of MOOC platforms provides students with accessible, comprehensive, and efficient channels for learning [13, 14].

The paper contributes to educational reform by leveraging the capabilities of Internet technology to address the unique characteristics of students in intercultural communication classes [15, 16]. A notable feature is the growth of enormous open online course system specifically tailored for English-inter-cultural communication-classes, incorporating neural-networks to enhance the learning experience [17, 18]. This innovative system exchanges in-person instruction combined with online classroom learning, offering flexibility in time and location [19].

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The paper outlines the advantages of the MOOC system, including its open educational resources and scalability, positioning it as a pivotal component in modern education. The proposed innovations hold promise for advancing individual capacity and social development, setting the stage for effective educational reform in the classroom [20].

The major contribution of this work is summarised as follows,

- The manuscript proposes the novel combination of improve the teaching quality of MOOC English course using Hamiltonian Deep Neural Network (HDNN).
- Analysis and optimization of social behaviour of college students using Hierarchical Message-Passing Graph Neural Networks (HMP-GNN) is proposed. This integration aims to improve the teaching quality.
- Dataset are collected from the "Dataset of manual web accessibility evaluation of English-language massive open online courses in adult basic life support".
- Pre-processing using the Switching Hierarchical Gaussian Filter method was employed to clean the dataset.
- The HDNN method was employed to enhance the teaching quality of the MOOC English course, while the COA method was utilized to optimize the weight parameters of the HDNN method
- Then, the proposed technique is simulated utilizing Python and compare then other existing methods.

The rest of the manuscripts are arranged as below: sec. 2 reviews the literature study, sec. 3 provides MOOC system for English Intercultural Communication Course (EICC), sec. 4 presented the proposed method, and sec. 5shows the result and discussion, and in sec. 6, the manuscript concludes.

II. METHODOLOGY

Among the numerous research works related to improve the teaching quality of MOOC English Courses using deep learning, some current research works are reviewed here.

Jiang and Hou [21] have suggested to discover the application and growth of the neural network-based MOOCs system for the English course on cross-cultural communication. First, the general function components of the MOOC system were explained; with a focus on the system database design, student function module, administrator function module, and teacher functional module, for EICC. Second, principal component analysis was used to select the teaching quality indicator of MOOC system in EICC, while a genetic algorithm served as the foundation for the teaching methodology of the system.

Hao and Wei [22] have suggested the MOOC-based blended college English teaching strategy by developing a mechanism for teaching evaluation. The key index in the teaching mode was then extracted after the K-modes algorithm was improved using the co-occurrence rate index. The prediction models of the student learning impact taken into account both the benefits and drawbacks of the teaching style, was created using a neural network. As a result, the models have high prediction accuracy and appropriately capture the issues present in the teaching model, suggesting that the teaching evaluation model has a positive assessment impact.

Zhao [23] discussed the general configuration of an intelligent teaching fed MOOC system, thoroughly examines the functional and system needs, and gains a deeper understanding of the theoretic underpinnings and technical requirements needed by the system. Thorough examination of the MOOC system's intelligent teaching assistant modules, use case analysis, architecture, technology, and system functions; identifying the purpose of each module; setting up a database management system; introducing the teaching quality evaluation system depending on BPNN; and implementing the system design and test.

Mi [24] has developed a hybrid approach for MOOC cheating detection based on deep learning. By including CNN, the model significantly enhances the detection performance of a single model. An attention mechanism with a bidirectional gated recurrent unit. To confirm the algorithm's effectiveness, the presented model chooses data from a MOOC platform's English learning behaviour.

Yasar and Polat [25] have investigated how they view a MOOC-related FC model and how it affected their academic performance. This makes the study an intriguing chance to further our understanding of the FC model based on MOOCs in teacher education, particularly in the area of ELT. During the 2019–2020 academic years, the study was conducted at a state institution in Turkey with twenty-seven pre-service language instructors. A mixed-methods study design was the methodological approach, which benefited from both qualitative and quantitative data collection methods. It employed a one-group pre-test - post-test pre-experimental study design.

Huiying and Qiang [26] have analysed and enhanced traditional MOOC, refines traditional algorithms with the real requirements of MOOC teaching, and introduced a novel, improved model with the goal of increasing the effectiveness of college English cross-cultural instruction based on cloud computing and artificial intelligence technologies. In addition, this post uses needs analysis to construct up functional modules.

Gong and Zhou [27] have provided a decision tree algorithm depending on data mining and look at the improved decision tree technique. Thirteen pupils, or thirty-four percent of the total, thought the new teaching technique was particularly effective. A total of 25 students found that this style was beneficial for providing in-depth understanding of the fundamentals.

III. ENGLISH FOR INTERCULTURAL COMMUNICATION COURSE MOOC SYSTEM

A MOOC is a publicly accessible web-related online training program designed for large collections of students from diverse positions. Although, these courses cannot offer academic credits continuously, and they often gives a certification, enhance employment prospects, or pave the way for further study. While MOOCs have traditionally been associated with higher education and professional development, MOOCs have become the new norm in many public institutions and undergraduate degree programs because of the effect of the coronavirus pandemic, the landscape has changed. The system of MOOC for the EICC is structured into four main modules: the intercultural communication course resource management module, the login control module, intercultural-communicative interactive-learning module, and system management module, in accordance with system requirements. The function of online teaching allows teachers or administrators in the MOOC system to broadcast and update statements related to the EICC in the News Centre. This includes information on other college news, online teaching links, and the provision of student access and references for learning. The interactive-learning function is a fundamental parameters of MOOC systems and encompasses discussion and answer functions within the EICC. This facilitates the creation of a learning network between students and enhances communication amid pupils and instructors. The function of system management addresses characteristics such as simplicity, resource sharing, and multiuser access within the MOOC system. Considerations for data security and role differences necessitate the inclusion of user information management, role administration, and security administration functions in the system settings. In summary, the MOOC system for EICC comprises various function modules, with a focus on the administrator function module, teacher function module, and student function module, within the overall framework of the MOOC system.

A. Analysis of Student Module

With the help of this module, pupils will be able to learn more methodically and efficiently. It is an instructional resource that has been painstakingly created and offers a number of well-planned learning opportunities to help students understand certain learning goals. The system may be divided into front and background structures by analyzing the MOOC system module as previously said. The foreground pertains specifically to English cross-cultural communication students, offering tailored features for their educational needs. Meanwhile, the background structure is designed to enable administrators to effectively implement and maintain the MOOC scheme. The Course Centre allows students to access online learning within the MOOC system. After logging in, students can engage in online learning activities and evaluate their progress in the courses. The Resource Centre provides students with the ability to search for English intercultural communication-related content, courseware, and another teaching resource using keywords. They can then download the resources they need for their studies. Within the Personal Centre module, students can view individual information, review exercise learning and plans progress, post comments and topics, and participate in chat rooms through provided links. This module aims to enhance the personalized learning experience for each student within the MOOC system.

B. Analysis of Teacher Function Modules

By using hyper-links, if the standards are accessible online or expressing the principles in the sections of learning goals, this module allows educators to make direct linkages to curricular standards and guidelines. A possibility to research, compiles, generates, and develops new knowledge and abilities may be found in MOOCs. Consequently, educators, whether pre-service or in-service, may develop a more inventive and diversified viewpoint that strengthens their teaching stance. The teacher module is broken down into five sections: the homepage, news centre, resource centre, personal centre, and course centre.

- **Personal Centre**

Students get access to a customized hub where they may manage personal information, evaluate workout regimens, and monitor their progress in learning using the MOOC system's "Personal Centre" module. Teachers may access their published material, related courses, and instructional resources via a personal center module. Chat rooms are also accessible to teachers.

- **Resource Centre**

Resource centre facilitate information sharing and may support a range of active learning activities. Teachers may access and contribute educational content to the MOOC system after signing in.

- **Course Centre**

Upon logging onto the EICCMOOC system, instructors may examine and post the courses as well as respond to student inquiries.

- **News Centre**

The news portion of the system contains information that instructors with access to the EICC MOOC program may see and browse. Additionally, it may promote other pertinent material and the English intercultural communication training.

- **Homepage**

A main purpose of homepage is to direct people through our system, thus it is essential that consumers be able to do so with ease. Make a clear division between the options and possess a firm understanding of the underlying relationships. In the MOOC system's interface, educators with teaching powers input usernames and passwords for courses on English intercultural communication. The home page of MOOC system for the EICC loads after a successful login.

C. Analysis of the Administrator Functions

The Administrator module of MOOC system, which is designed for English Intercultural Communication courses, is divided into seven useful sections: system maintenance, teacher supervision, course administration, resource management, user management, and news management. The several features that administrators use for efficient administration and supervision inside the MOOC system are reflected in this division.

- **Homepage**

The Home Page Entering the login and password, the administrator accesses the MOOC system page of EICC. The first page of the website displays administrator, and they click to access the background administration interface.

- **User Management**

The MOOC system administrator may add or remove users, manage regular users, and change certain processes.

- **News Management**

The administrator has the authority to disseminate and maintain campus news in accordance with the advancement of English language instruction pertaining to cross-cultural communication.

- **Course Management**

Administrators should check the file size, format, and authenticity of the instructional videos submitted to the system before publishing video courses for students to study. Administrators should also change the front-end display video list based on the effectiveness of English cross-cultural communication education after receiving clearance.

- **Resource Management**

The method by which businesses effectively manage their vast resources is known as resource management. Both material and intangible resources may be present. To allocate the right resources to the right tasks, planning is necessary. Resource management includes budgets and plans for personnel, activities, supplies, and technology. The administration of resources in our system is similar to the course management mentioned before.

- **Teaching Supervision**

It is not the responsibility of MOOC system administrators to keep a close eye on students' progress, promptly identify any remarks or material posted in the system unrelated to EICCs, and take appropriate action against major offenders.

- **System Maintenance**

The word "system management" refers to a broad category of computer maintenance that is required to maintain a system operational. The two basic parts of maintenance services are preventive and corrective maintenance. To ensure that the MOOC system for the EICCruns steadily, system administrators must do irregular system maintenance, identify issues early, analyse, and resolve them completely.

IV. PROPOSED METHODOLOGY

In this research, MOOCEC-HDNN for improve the teaching quality of MOOC English Course. Initially the inputs are gathered from the English-language MOOCs teaching ABLS, they involve cleaning and preparing the data to improve the using Switching Hierarchical Gaussian Filter. Then they use Hamiltonian Deep Neural Network to improve the teaching quality of MOOC English course. Finally, COA is employed to optimize the weight parameter of HDNN. Figure 1 portrays the Block Diagram of Proposed MOOCEC-HDNN
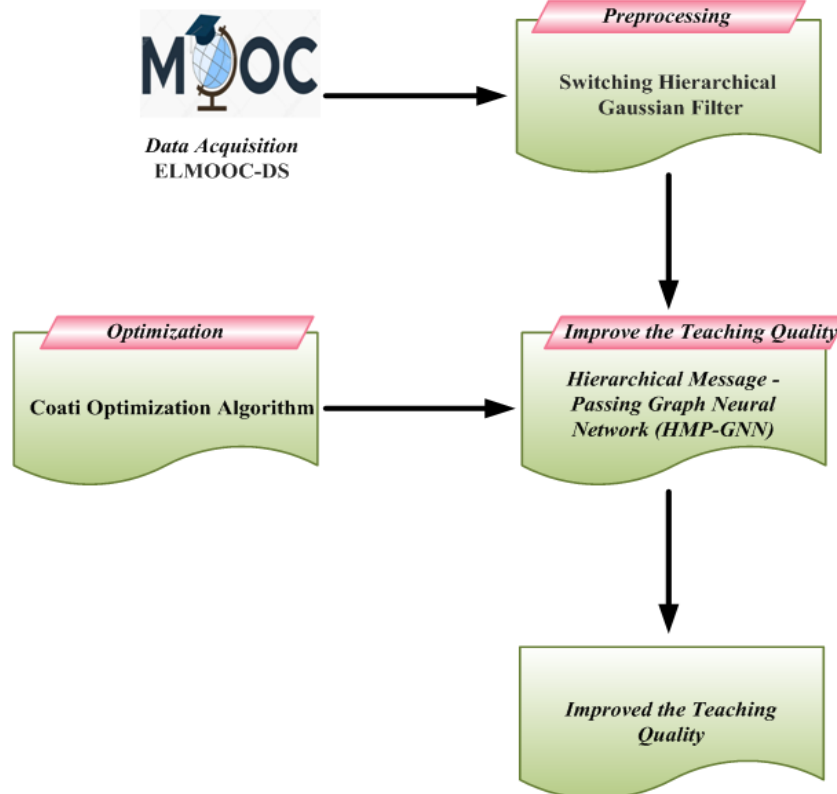

Figure 1: Block Diagram of Proposed MOOCEC-HDNN

A. Dataset Description

The web accessibility of English-language MOOCs (ELMOOCs) teaching Adult Basic Life Support (ABLS), several datasets capture these manual evaluations, offering valuable insights into the quality and accessibility of these online learning resources [28]. One prominent example resides on Mendeley Data, where researchers meticulously assessed ABLS MOOCs against established resuscitation guidelines and accessibility standards. This dataset provides a treasure trove of information, including general MOOC characteristics, detailed evaluation results, and even abbreviation explanations. While this specific dataset dates back to December 2021, it paves the way for further investigation and comparison with newer MOOCs. Additionally, accessibility testing tools and research publications can offer complementary data points and methodologies, enriching your understanding of ABLS MOOC accessibility. Carefully scrutinize the available options and their associated methodologies before embarking on your exploration of this crucial domain.

B. Pre-processing using Switching Hierarchical Gaussian Filter

To apply the Switching Hierarchical Gaussian Filter (SHGF) for data analysis, it is essential to start by obtaining a relevant dataset, which may include information about MOOC course or any other data suitable for the analysis. Once a suitable dataset is obtained, the first step is data cleaning and preparation. Various techniques such as imputation, filtering, and normalization can be applied to make the data suitable for further

analysis [29]. After data cleaning, the next step is to apply the Switching Hierarchical Gaussian Filter (SHGF). SHGF is a statistical mode used for filtering time-series records to estimate underlying states and parameters. Applying SHGF to the cleaned data involves setting up the model parameters, selecting appropriate state and parameter transition models, and using Bayesian estimation techniques for inference. Once the SHGF analysis is performed, researchers can gain insights into the underlying patterns, trends, or states within the data. The results obtained from the SHGF analysis can then be used for various purposes, such as prediction, decision-making, or further research. As always, when conducting any analysis, it is crucial to validate the results, interpret them correctly, and consider the limitations and assumptions of the chosen methodology. Additionally, researchers should keep abreast of the latest developments in SHGF or any other data analysis techniques beyond my last update to ensure they are using the most up-to-date methodologies for their research.

The state transition model represents how the underlying state evolves over time. In the context of SHGF, this could be a linear or nonlinear model. For a simple linear model, it is specified in eqn (1)

$$x\_\{t\} = A * x\_\{t\text{-}1\} + w \tag{1}$$

Consider $x\_\{t\text{-}1\}$ specifies state vector at $t\text{-}1$ time (previous time step), $x\_\{t\}$ specifies state vector at t time, w is the process noise or system noise, assumed Gaussian with zero mean, and A implies the matrixes of state transition that demotes the evolution of states. The observation model relates the observed data to the underlying state. In SHGF, this is a linear or nonlinear model depends on the application. For a simple linear model, it is depicted in equation (2)

$$y\_\{t\} = H * x\_\{t\} + v \tag{2}$$

Where $y\_\{t\}$ the observed data or measurement at time t, H signifies observation matrix that maps state to observation space, v signifies observation noise, assumed to be Gaussian with zero mean. SHGF utilizes Gaussian distributions to model the uncertainties in the state transition and observation processes. These distributions are commonly represented in equation (3)

$$P(x\_\{t\} \,/ x\_\{t\text{-}1\}) \sim N(A * x\_\{t\text{-}1\}, \, Q) \tag{3}$$

Here $P(x\_\{t\} \,/ x\_\{t\text{-}1\})$ denotes probability distribution at time, t given the state at time $t\text{-}1$, Q is the covariance matrix representing the process noise and is determined in equation (4)

$$P(y\_\{t\} \,/ x\_\{t\}) \sim N(H * x\_\{t\}, \, R) \tag{4}$$

Here $P(y\_\{t\} \,/ x\_\{t\})$ implies the probability distribution at time t given the state at time t, R implies the covariance matrix representing the observation noise. SHGF employs Bayesian estimation to update the beliefs about the underlying state based on new observations. The estimation process involves computing the posterior dissemination of the state specified the annotations using Bayes' theorem shown in equation (5)

$$P(x\_\{t\} \,/ y\_\{1:t\}) = (P(y\_\{t\} \,/ x\_\{t\}) * P(x\_\{t\} \,/ y\_\{1:t\text{-}1\})) / P(y\_\{t\} \,/ y\_\{1:t\text{-}1\}) \tag{5}$$

Here $P(x\_\{t\} \,/ y\_\{1:t\})$ denotes posterior distribution of state at t time specified all the observations up to time t, and $P(y\_\{t\} \,/ y\_\{1:t\text{-}1\})$ implies the likelihood term that acts as a normalizing constant.

Finally, before applying the Switching Hierarchical Gaussian Filter (SHGF) for further analysis, thorough cleaning and preparation of the dataset are essential to enhance data quality and suitability. Proper data cleaning can help address missing values, outliers, and inconsistencies, ensuring that the SHGF algorithm can work effectively and provide meaningful insights. By conducting data cleaning as a preliminary step, researchers can maximize the accuracy and reliability of the SHGF analysis and draw more robust conclusions from the processed data.

C. MOOC English Course Teaching Quality Improvement by using Hamiltonian Deep Neural Network

In this section, that proposed improve the teaching quality using Hamiltonian Deep Neural Network (HDNN) [30] is discussed. The weighted quantity of the input EICC data, after the activation-function of hidden-layer use is what makes up the output layer of the neural network.

Thus, it is given an equation (6)

$$x(t) = g(x(u), \theta(u)), \qquad 0 \le u \le U \tag{6}$$

Here, $x(t)$ represents the measure of teaching quality at time, g is represents the function that encapsulates the relationship between the input $x(u)$ and the parameter of $\theta(u)$ in the context of teaching quality improvement.

Here, $\in \Re^n$, $x(0) = x_0$ and $\theta(u) \in \Re^{n\theta}$ implies the parameters of vector. For Identifying deep neural network (DNN)design, discretize with sampling periods $h = \dfrac{T}{N}$, $N \in N$ and make use of the generated discrete-time equations to define every N network layer. Thus, it is given an equation (7)

$$x(t) = K(u)\frac{\delta I(x(u),u)}{\delta x(u)}, \qquad x(0) = x_0 \tag{7}$$

Where $K(u) \in \Re^{n \times n}$ is skew-symmetric $K(u) = -J^T(u)$ at all times and t possibly related to teaching quality or some other metric. To recover the DNNs method, the following is the Hamiltonian function. Thus, it is given an equation (8)

$$H(x,t) = \sigma(W(t)x + b(t))^T 1_n + \eta(t)^T x + \alpha Q(x,t) \tag{8}$$

Here, $Q(x,t)$ represents q quality of matric with teaching process, capturing factor like the effectiveness of communication, course material, and the term $\alpha Q(x,t)$ indicates that the Hamiltonian is influenced by the teaching quality metric. α is a scaling factor that controls the strength of the influence of the teaching quality metric on the HDNN. This adaptation implies that the Hamiltonian now takes into account both the neural network dynamics represented by the terms involving $\bar{\sigma}(W(t)x + b(t))^T 1_n$ and $\eta(t)^T x$ as an additional term related to teaching quality improvement $\alpha Q(x,t)$. The goal is to have the system dynamics influenced not only by the neural network architecture but also by the quality of teaching in the context of English communication in a MOOC based course

$$|\sigma'(y)| \le R \tag{9}$$

Here, $\sigma'(y)$ is represent any of the sub-derivative. This assumption holds for common activation functions, like the logistic function, $\mathrm{Re}LU(.)$ and $\tanh(.)$, $\mathrm{Re}LU(.)$. Thus, it is given an equation (10)

$$\theta^{(l+1)} = \theta^{(l)} - \gamma \cdot \nabla_{\theta(l)} K, \tag{10}$$

Here, l is represent the iteration number $\gamma > 0$ implies the step-size of optimization and the element of $\nabla_\theta K$ represent every iterations in the gradient of the loss function K based on the needs of the parameters. Finally the HDNN is improved the teaching quality. Crisscross Harris Hawks Optimization Algorithm is HDNN classifier. In this work, COA is used to enhance HDNN weight parameter θ and σ. Here, COA is used for tuning the weight and HDNN bias parameter.

D. COA Algorithm based Optimization

The COA is also called new meta-heuristic algorithm. This mimics the natural behaviour of coati [31]. The basic aim of COA method is the recreation of the two behaviours of coati in nature: (i) their actions when attacking and hunting the iguanas and (ii) their escape from the predators.

Step 1: Initialization

Initiate the COA by initializing the population of potential solutions, often termed 'coatis.' This can be achieved through either random initialization or a predefined strategy.

$$Population\ of\ candidate\ solutions = \begin{bmatrix} y_{11} & y_{12} & y_{13} & \cdots & y_{1D} \\ y_{21} & y_{22} & y_{23} & \cdots & y_{2D} \\ & & \ldots\ldots & & \\ y_{n1} & y_{n2} & y_{n3} & \cdots & y_{nD} \end{bmatrix} \tag{11}$$

Let the population of Coati Optimization Algorithm (COA) is initialized as y, and its respective positioning as y_n.

Step 2: Generating in random

Afterward initialization, input parameters developed at random.

Step 3: Calculation of Fitness

The fitness is depends on the objective function, and is described by,

$$F = Optimize' \theta \, and \, \sigma' \tag{12}$$

Step 4: Exploration Phase

Replicating their assault plan on the iguanas serves as the basis for the 1ˢᵗ step of upgrading the Coati population in the search-space. This tactic involves a pack of coatis scaling the tree to get close to an iguana and frighten it. Also, a few additional coatis will remain behind the tree till the iguana drops to the ground. Then, the coat is assault and pursue the iguana once it falls to the ground. The below equation may be used to numerically approximate the location of the coatis ascending from the tree.

$$V_i^{P1} : v_{i,j}^{p1} = v_{i,j} + d.\left(Iguana_j - I \cdot v_{i,j}\right), for \, i = 1,2,\ldots\ldots\left[\frac{N}{2}\right] \tag{13}$$

$$and \quad j = 1,2,\ldots\ldots,m.$$

The below eqns. Shows the Coati on the ground movement in search-space, which is simulated based on this random location.

$$Iguana^C : Iguana_j^C = lb_j + d.\left(ub_j - lb_j\right), j = 1,2,\ldots.m. \tag{14}$$

$$V_i^{P1} : v_{i.j}^{p1} = \begin{cases} v_{i,j} + d.\left(Iguana_j^G - I.v_{i,j}\right), & F_{Iguana^G} < F_i, \\ v_{i,j} + d.\left(v_{i,j} - Iguana_j^G\right), & else, \end{cases} \tag{15}$$

$$for \, i = \left[\frac{S}{2}\right] + 1, \left[\frac{S}{2}\right] + 2, \ldots, S \quad and \quad j = 1, 2, \ldots.m.$$

The updated condition for i = 1, 2,…, S simulated using Eq. (21)

$$V_i = \begin{cases} V_i^{P1}, & F_i^{P1} < F_i, \\ V_i, & else. \end{cases} \tag{16}$$

Here $Iguana$ represents the location of the iguana inside the search-space is really the positions of optimum member, $Iguana_j$ is its j th dimension; V_i^{P1} implies the novel position measured for the i th coati, $v_{i.j}^{p1}$, F_i^{P1} is its j th dimension, and objective function values; d implies the random real number in [0, 1]; I implies an integer, which generated randomly from{1,2} set, $Iguana_G$ implies the iguana position on the ground, which is generated randomly, $Iguana_j^G$, F_{Iguana^G} is its j th dimension and objective function value; and $[\bullet]$ implies the function of floor.

Step 5: Phase of Exploitation

A mathematical model of coati natural behavior while interacting with and evading predators is used to simulate the second step of the processes of updating coati location in the search-space. From its location, an animal flees, and predator attacks a coati. By using this tactic, Coati has managed to secure a position that is secure and near to its present location, demonstrating the capacity of COA for local search exploitation.

Using Eqns. (17) and (18), a random position is created close to each coati's location to replicate this behavior.

$$LB_j^{local} = \frac{LB_j}{T}, UB_j^{local} = \frac{UB_j}{T}, where \, T = 1,2, \ldots,T. \tag{17}$$

$$A_i^{P2} : a_{i,j}^{P2} = a_{i,j} + (1 - 2d) \cdot \left(LB_j^{local} + d.\left(LB_j^{local} - LB_j^{local}\right)\right), \tag{18}$$

$$i = 1, 2, \ldots, S, \quad j = 1, 2 \ldots, m,$$

If the newly computed location increases the value of the goal function, which this condition uses Eqn. (19) to mimic, then it is acceptable.

$$A_i = \begin{cases} A_i^{P2}, & F_i^{P2} < F_i, \\ A_i, & else, \end{cases} \tag{19}$$

From the above equation, depending on the 2nd phase of COA, A_i^{P2} implies the novel position measured for the i thcoati, $a_{i,j}^{P2}$ and F_i^{P2} is its j th dimension, and objective function value; d implies a random number in [0, 1], UB_j^{local} and LB_j^{local} are the local upper and lower limits of the j th decision variable, UB_j and LB_j implies the upper and lower limits of the j th decision variable, and T is the iteration counter.

Step 6: Update the Best Solution

An iteration of a COA ends when every coatis location in the search-space has been updated depending on the 1st and 2ndphases.

Step 7: Termination Criteria

The expected outcome will come means the process will be terminated. Otherwise step 3.

V. RESULT AND DISCUSSION

The experimental result of proposed MOOCEC-HDNN method is discussed in this section.. Then, proposed technique is simulated utilizing Python under several performance metrics. The obtained outcomes of proposed MOOCEC-HDNN are compared with existing MOOCEC-CNN [21], MOOCEC-GA-NN [22] and MOOCEC-KMA-NN [23] models.

A. Performance measures

Performance of proposed approach is articulated utilizing the Teaching Efficiency, Robustness Gain, and teaching quality Performance metrics.

1) Teaching Efficiency

Teaching Efficiency is the effectiveness of instructional methods in achieving educational goals relative to the optimized use of resources.

$$T_\eta = \frac{Learining\ outcomes}{\mathrm{Re}source\ Invested} \times 100$$

(20)

Here, *Learining outcomes* could be measured in terms of students performance, improvement in skills or any other relevant educational achievement, $\mathrm{Re}source\ Invested$ might include time, money, teaching materials, or any other resources used in the teaching process.

2) Robustness Gain

Robustness Gain is a metric that quantifies the improvement in system performance or resilience under perturbations or uncertainties compared to its performance under normal conditions.

$$R_G = \frac{Performance\ under\ normal\ Condition}{Performance\ under\ perturbed\ Con\ perturbed\ conditions}$$

(21)

This ratio provides a measure of how well the system maintains its performance in the presence of disturbances or uncertainties.

B. Performance Analysis

Figure 2 to 7 depicts simulation outcomes of proposed MOOCEC-HDNN technique. Then, the MOOCEC-HDNN is compared with three existing MOOCEC-GA-NN [21], K-12-ML-PTL-UA [22] and FNN-PTL-UA [23] models respectively.
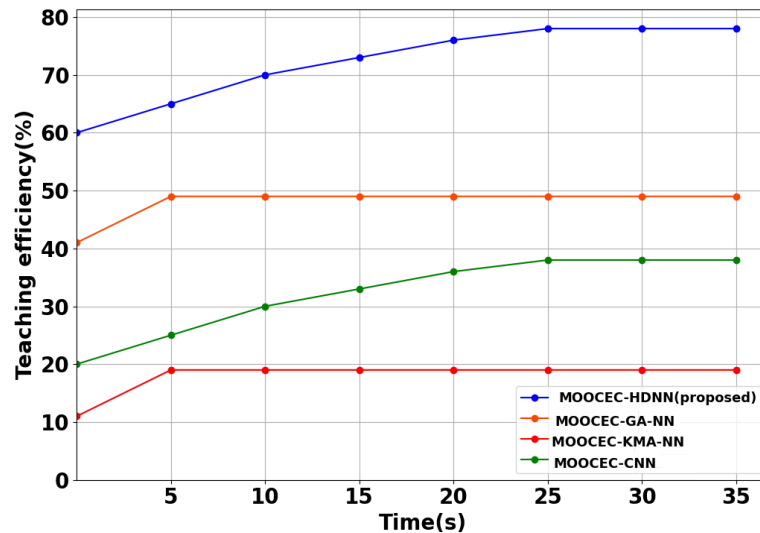
Figure 2: Comparative of teaching efficiency with existing and proposed techniques

Figure 2 depicts the comparative of teaching efficiency with existing and proposed techniques. Initially, the efficiency of the proposed method is starts with 60% then they increases to 78% at 0 to 35 sec. From 42%, the efficiency value is initially starts then at 0 to 5 sec, it slightly increases to 48%, then they remain efficiency value is constant at 5to 35 sec. From 11%, the efficiency value is initially starts at 0 sec then at 0 to 5sec, it slightly increases to 18%, they main efficiency value is constant at 5 to 35 sec. From 20%, the efficiency initially starts at 0 sec then at 0 to 35 sec, it slightly increases to 38%. Thus, the teaching efficiency of the proposed method is optimal than the existing techniques.
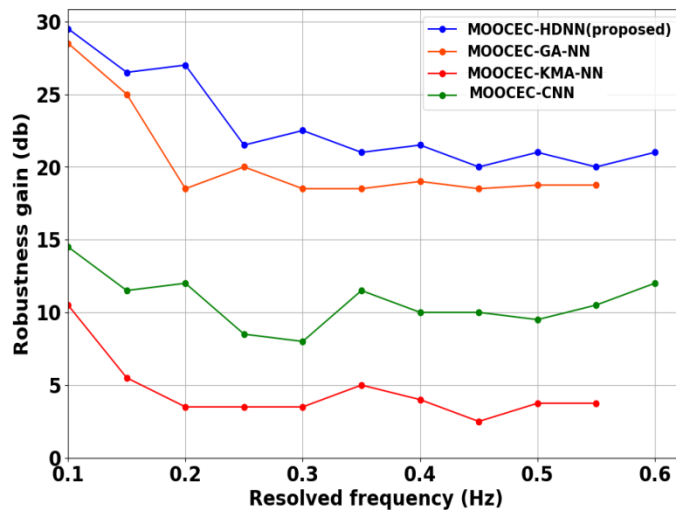

Figure 3: Comparative of robustness gain value with existing and proposed techniques

Fig 3 depicts the comparative of robustness gain value with existing and proposed techniques. The robustness value of the proposed method is initially starts from 28dB at 0.1Hz, and then at 0.1 to 0.6Hz, they slowly reduce to 21dB. The robustness value of the proposed method is initially starts from 27dB at 0.1Hz then at 0.1 to 0.52Hz, it slowly reduced to reach 21dB. The MOOCEC-KMA-NN method robustness value is initially starts from 11dB at 0.1Hz then they slowly reduced to reach 3dB at 0.1 to 0.52Hz. The MOOCEC-CNN method robustness value is starts from 15dB at 0.1Hz then they slowly reduced to reach 13dB at 0.1 to 0.6Hz.Thus, the teaching efficiency of the proposed method is optimal than the existing techniques.
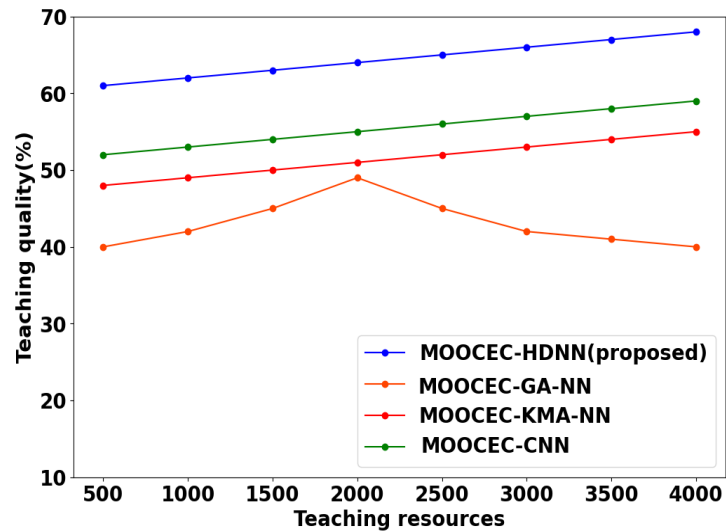
Figure 4: Comparative of teaching quality improvement with existing and proposed techniques

Figure 4 depicts the comparative of teaching quality improvement with existing and proposed techniques. The teaching quality value of the proposed method is initially starts from 60% at 500 teaching resources then at 500 to 4000 teaching resource, it slightly increases to 68%. The MOOCEC-CNN method teaching quality value is starts from 40% at 500 teaching resources then they slightly increases to 48% at 500 to 2000 teaching resource they slowly reduced to reach 40% at 2000 to 4000 teaching resource. The MOOCEC-GA-NN method teaching quality value is initially starts from 48% at 500 teaching resources then they slightly increases to 55% at 500 to 4000 teaching resource. The MOOCEC-KMA-NN method teaching quality value is initially starts from 52% at 500 teaching resource then they slightly increases to 58% at 500 to 4000 teaching resource. Thus, the teaching efficiency of the proposed method is optimal than the existing methods.
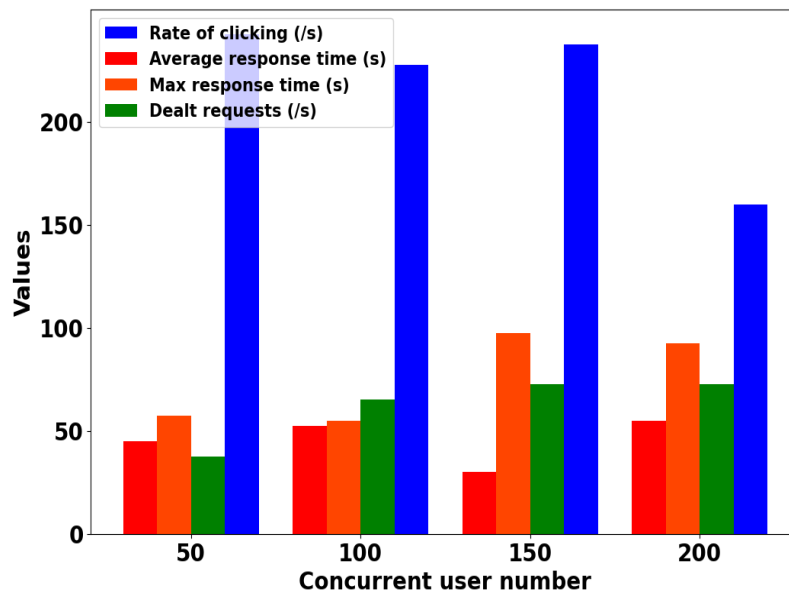

Figure 5: Analysis of System's efficiency

Analysis of System's efficiency is shown in Figure 5. For 50 users the rate of clicking value is 280, average response time is 48, maximum response time is 52 and the dealt requests value is 46. For 150 users the rate of clicking value is 260, average response time is 45, maximum response time is 42 and the dealt requests value is 80.
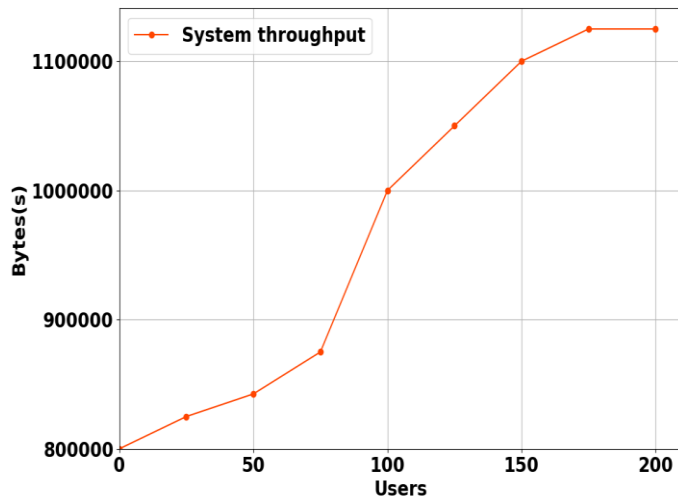
Fig 6: Analysis of handling capability for system throughput

Analysis of handling capability for system throughput is shown in Figure 6. The system throughput value is initially starts from 800000 bytes at 0 users then it slightly increases to 1150000 at 0 to 200 users.
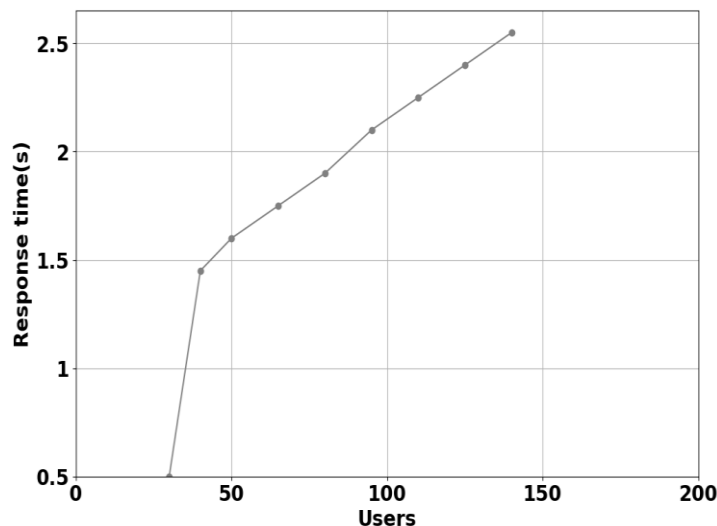

Figure 7: Analysis of handling capability for response time

Figure 7 depicts the analysis of handling capability for response time. The response time is starts from 0.5s at 40 users then at 0 to 140 users, the value slightly increases to 2.6 s.

VI. CONCLUSION

In conclusion, the efficiency of MOOCEC-HDNN technique is utilised to improve the teaching quality of MOOCs English course. Employing HMP-GNN and COA, the method achieved superior performance compared to existing models like MOOCEC-GA-NN, MOOCEC-KMA-NN, and MOOCEC-CNN methods. The proposed LPWSN-DSRNN-MOA method is implemented in python platform using ELMOOC-DS dataset. The implemented method is executed using python and the proposed MOOCEC-HDNN method higher teaching efficiency of 78%, Robustness Gain of 28dB and teaching quality 68% while comparing other existing methods.

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