ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

EXPLORING THE DYNAMICS OF EDUCATIONAL FEEDBACK NETWORKS WITH GRAPH THEORY AND LSTM-BASED MODELING FOR ENHANCED LEARNING ANALYTICS AND FEEDBACK MECHANISMS

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ABSTRACT

The promise of learning analytics to transform education by offering insightful data on student learning patterns and enabling personalized feedback mechanisms has attracted a lot of interest in recent years. In order to improve learning analytics and feedback mechanisms, this study uses graph theory and Long Short-Term Memory (LSTM) based modelling to analyze the dynamics of educational feedback networks. The study makes use of a sizable dataset made up of educational interactions from various learning settings, including student contributions, evaluations, and teacher comments. A network model of these interactions is created using graph theory, where nodes stand in for students, teachers, and educational materials, and edges for feedback linkages. This network-based strategy makes it possible to see the educational environment as a whole and makes it easier to analyze feedback dynamics. Furthermore, taking into account the sequential character of educational encounters, LSTM-based models are created to represent temporal relationships within the feedback networks. These models allow for the evaluation of feedback quality, the identification of influential nodes, and the prediction of future feedback patterns. A thorough foundation for comprehending the complex dynamics of educational feedback networks is provided by the combination of graph theory with LSTM-based modelling. This paper gives a distinctive viewpoint on the evaluation of educational feedback networks by fusing graph theory with LSTM-based modelling. The suggested framework has the power to improve educational practices, guide selections for instructional design, and encourage student achievement.

Keywords: *Learning analytics, graph theory, LSTM*

1. INTRODUCTION

The use of technology in education has created new opportunities to comprehend and enhance the learning process. The study of educational data gathered from digital platforms has enormous potential for revealing trends in student performance, behavior, and the efficiency of instruction [1]. In recent years, there has been a lot of interest in the topic of learning analytics, which uses educational data to support decision-making and improve educational results. Studying educational feedback networks, which include the flow of feedback between students, teachers, and educational resources, is a crucial component of learning analytics. Feedback networks illustrate the information flow within an educational environment by illustrating the interwoven interactions created by the giving and receiving of feedback. Researchers and educators are able to enhance the learning process overall by studying the dynamics of these feedback networks, which will help them better understand how effective feedback mechanisms are [2].

The dynamics of feedback networks may be thoroughly explored and understood thanks to graph theory. It can be difficult to analyze and comprehend feedback networks, which include the flow of feedback between various entities including students, teachers, and educational resources. To examine the complexity of these networks, however, graph theory offers a strong framework [3]. Using graph theory, researchers may analyze the structure and characteristics of a feedback network by visualizing the interactions and connections as nodes and edges, respectively. It provides a collection of mathematical methods and tools for examining the connections between nodes, their centrality and clustering, as well as the patterns and routes of information flow. Researchers can get important insights into the feedback dynamics in an educational setting by using the lens of graph theory [4]. They can recognize important nodes that are crucial for feedback transmission or reception, comprehend the efficacy of information spread, and investigate how network topologies affect the efficiency of feedback.

Additionally, since the network can be seen and examined as a whole, graph theory gives a comprehensive picture of the educational environment. This all-encompassing viewpoint enables researchers to see the linkages and relationships between various parts, giving them a better grasp of the intricate feedback processes at work. For analyzing and interpreting the dynamics of feedback networks, graph theory is a vital tool. It makes it easier to analyze network topology, information flow, and the impact of certain nodes, which eventually helps us comprehend feedback more thoroughly in the context of education [5].

LSTM-based models are used to represent the temporal correlations present in feedback networks. Recurrent neural network architectures such as LSTM have shown to be efficient in handling sequential data, including time-series data and sequential interactions [6]. The sequential dependencies prevalent in feedback networks are difficult for traditional feed forward neural networks to grasp. To overcome this problem, LSTM models include memory cells and specialized gates that provide them the capacity to store and selectively forget information over time. LSTMs can represent long-term dependencies and capture temporal connections in the data because of this. Researchers may study how feedback develops and plays out over time by applying LSTM-based models to feedback networks. These models are capable of identifying repeated feedback sequences, pattern and trend detection, and providing insights into the dynamics of feedback interactions [7].

By taking the temporal context of the feedback's delivery into account, LSTM-based models make it easier to evaluate the quality of the feedback [8]. As a result, they can provide important information about the significance and potency of feedback from various sources by identifying prominent nodes or entities in the network. Additionally, LSTM models may be used to forecast future feedback patterns based on previous sequences, providing predictive capabilities that can be used to direct decision-making and influence instructional design. The temporal correlations found in feedback networks can be captured by researchers using LSTM-based models [9]. With the help of these models, it is possible to analyze sequential data, spot trends, and get a greater understanding of how feedback interactions change over time.

The purpose of this study is to analyze the dynamics of educational feedback networks by combining graph theory with LSTM based modelling [10]. For expressing and analyzing complex networks, such as educational exchanges, graph theory offers a reliable foundation. Researchers may acquire a comprehensive understanding of the educational environment and reveal underlying patterns and structures by building a network where nodes represent students, teachers, and educational materials and edges indicate feedback links. The study is further improved by the use of LSTM-based modelling since it can capture the temporal relationships inside the feedback networks. The nature of educational encounters is innately sequential, with feedback changing over time. Recurrent neural network models called LSTMs are particularly good at capturing long-term relationships and can forecast future feedback patterns based on previous interactions. Researchers can determine key nodes in the network, predict feedback trends, and assess feedback quality by utilizing LSTM models [11].

Exploring educational feedback networks using graph theory and LSTM-based modelling is an innovative way to use learning analytics [12]. By examining context and interactions within the educational ecosystem in addition to isolated feedback occurrences, this multidisciplinary approach offers a thorough understanding of the dynamics of feedback. This research has the ability to guide instructional design decisions, improve feedback allocation tactics, and ultimately improve

Journal of Theoretical and Applied Information Technology
15th January 2024. Vol.102. No 1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

the learning experience for students by revealing feedback patterns and dynamics. Figure 1 displays several learning statistics.

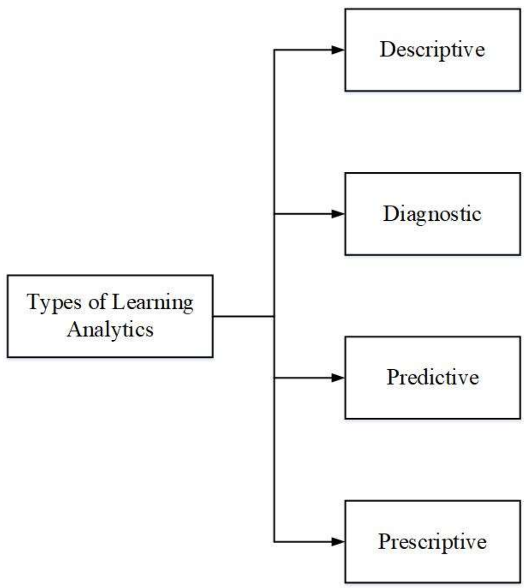

Figure 1: Types of Learning Analytics

In the realm of educational technology, this research endeavors to forge new frontiers by delving into the dynamics of educational feedback networks through the innovative lens of graph theory and LSTM-based modeling. By synthesizing these two powerful paradigms, this study aims to pioneer novel approaches for understanding and optimizing the intricate relationships within educational systems. The unique contribution lies in the creation of advanced learning analytics and feedback mechanisms, fostering a deeper comprehension of student progress, engagement, and knowledge acquisition. This research not only seeks to push the boundaries of traditional educational analysis but also envisions the development of more adaptive and personalized feedback systems, ultimately enhancing the efficacy of learning environments. The scope of this work extends to the intersection of artificial intelligence and education, promising to unveil insights that could revolutionize how we conceptualize, measure, and enhance the learning experience in contemporary educational settings.

This study examines the dynamics of educational feedback networks using graph theory and LSTM-based models. Understanding the intricacies of feedback within the educational environment would help researchers progress the field of learning analytics and improve feedback systems for improved educational results. The combination of graph theory with LSTM modelling provides a unique and complete way for assessing educational feedback networks, which has the potential to affect teaching methods, promote student participation, and improve academic achievement.

The key contributions of the paper is given below,

- Creation of a pioneering framework that combines graph theory and LSTM-based modeling for a comprehensive analysis of educational feedback networks.
- Exploration and clarification of intricate connections and feedback loops within educational systems, unraveling the dynamics that influence student learning.
- Development of advanced learning analytics tools that utilize insights from the integrated framework, providing a nuanced understanding of student progress and engagement.
- The development of adaptive and personalized feedback mechanisms, aiming to optimize individualized learning experiences.

This article has the following format. Section 2 examines pertinent work. In part 3, the problem statement is covered. The methodology of the article is described in Section 4. In Section 5, the effectiveness and dependability of the suggested strategy are evaluated and contrasted with accepted practices. Section 6 delivers a conclusion at the end.

2. RELATED WORKS

Mubarak et al. [13] analyzed the majority of students view identical instructional videos, analyzing the learning behavior of MOOC aficionados has emerged as a problem in the discipline of learning analytics. It is beneficial to do an extensive examination of these behaviors, investigate different learning styles for students, and forecast their success using MOOC course videos. The present research uses clickstream information obtained from videos to analyze an ongoing sequencing issue with categorization and forecast student achievement, a crucial challenge in decision-making, in order to better serve students. The present research uses LSTM on a collection of implied variables obtained from video clickstream analysis to forecast students' weekly performances and provide teachers the tools to design prompt techniques for intervention. Findings indicate the suggested model's rate of precision ranges from 82%

to 93% all over the duration of the weeks. In information from actual programmes, the suggested LSTM model performed 93% more accurately than standard ANNs, Logistic Regression, and SVM,

Due to the expanding accessibility to instructional big data, analytical modelling has grown in popularity in educational institutions over the past few decades at specific, LMSs at the majority of academic institutions provide access to a multitude of educational information. This was studied by Chen and Cui [14]. Prior studies into statistical analysis in educational institutions employing LMS activity information, nevertheless, failed to sufficiently account for behavior among students over time series. LSTM networks were used in the present research to analyze student's online behavioral activity utilizing their LMS information for predicting the beginning of academic achievement. LSTM networks with eight traditional ML classifications in regards to forecasting accuracy as evaluated by the region underneath the ROC curve in order to highlight the possible uses of the DL technique in predictive analytics. Findings show that prompt identification of at-risk pupils with a modest level of accuracy in predicting was effectively accomplished utilizing periodic data on click patterns and the DL technique. In comparison to ML classification algorithms, the DL technique demonstrated greater generality and better prediction accuracy.

In recognition of its benefits and advantages, the field of online learning is rapidly expanding and it is investigated by Yan et al. [15]. Learning via the internet has a lot of promise because to educational technology like learning data analysis, student the modelling process, and sophisticated systems for tutoring. Learning consciousness and scholastic interventions are two common intrinsic difficulties in numerous distance education programmes, especially in SPOL. The academic achievement of online students may be impacted by these obstacles. Learning data analysis are starting to offer enormous promise for addressing these obstacles. Nevertheless, using the conventional distance instructional design methodology makes it difficult to fully realize the promise of learning statistics. In order to assure information gathering and instructional linkage, the current research, concentrating on SPOL, suggests that instruction analytics needs to be integrated into the course designing learning loop. A cutting-edge learning architecture-analytics approach that demonstrates how analytics for learning and classroom learning design may complement one another to improve learning outcomes. A collection of instructional solutions are suggested for online instructors who want to employ learning analytics to reduce the learning obstacles in SPOL according to the suggested framework. A computer science curriculum is provided as an instance to demonstrate the early practices of such as analytics about learning in the overall instructional design loops by adhering to these suggested design approaches. Lastly, additional research regarding ways to create and assess educational platforms with analytics for learning is described.

A crucial aspect of exchanges in mixed education is sentiment development which was studied by Huang et al. [16]. Even while exchanges have received a lot of focus in online learning situations, there is a dearth of study on how sentiment changes during different conversations in blended learning settings. Therefore, the present research used continuous information from five phases of development of 38 graduate pupils enrolled in a course that used blended learning to analyze sentiment change at various engagement levels. The sentiments in multiple conversations were selectively mined using text mining methods, and ENA being then utilized to reveal sentiment variations during the blended learning process' five training phases. The results revealed that in mixed learning environments, negative attitudes were only weakly correlated with a number of other sentiments, including humorous, bewildered, and unbiased sentiments. The emotions of learners can shift from unfavorable to helpful especially in the context of in-depth conversations. Conversely, both joking-positive and joking-negative feelings had higher links in the sentiment networks created through social-emotion exchanges than each of the two degrees of contact. In particular, the shifts in overlap emotion highlight the very first collisions and sublimation, and steady phases of a mixed learning process. The findings of the present research showed that the views of learners changed from being positive to being confused or unfavorable to becoming perceptive.

LMSs are being used more often to manage, monitor, and analyze learning events by Aljaloud et al. [17]. Blackboard serves as one such extensively utilized LMS in global higher education organizations. This is because it has the ability to match evaluation procedures, pupil-pupil, and pupil-educator connections, with established objectives and pupil objectives. The present investigation sought to ascertain the role that specific KPIs determined by individual Blackboard interactions had in predicting their educational results. In a mixed-methods investigation, four DL algorithms for forecasting pupil achievement were examined. Data on seven basic preparatory courses were used to gather data. To determine potential predictive KPIs linked to the technological Blackboard report, they were examined utilizing an investigative methodology. To determine the degree in which these variables are linearly connected with pupil achievement measures, correlational examinations were carried out. The best technique amongst the four models evaluated, according to the findings, was a model for prediction that integrated CNN-LSTM. The key inference derived from this research is the fact that the combination CNN-LSTM strategy may result in solutions that enhance and increase the utilization of the Blackboard LMS in academic settings.

Dyulicheva considered the views of ML applications, particularly decision trees, random forests, and DL for educational information mining solutions and the establishment of learning analytics applications [18]. Upon the basis of the learning statistics of a few computing MOOCs, the capabilities of sentiment evaluation with the BERT deep modelling and grouping utilizing k-means with the various techniques to text vector processing are examined for the establishment for educational analytics programmes. Around 300 MOOC descriptions suggested grouping them in order to comprehend the content and ability instructions. 2365 phrases regarding the material and 1150 phrases containing the word "teacher" or its equivalents in order to identify pupil emotions and the most prevalent phrases used for describing problems that arise throughout learning.

Doleck et al. [19] measured the effectiveness of social educational networks in conversations that are a part of MOOCs with a traditional layout, including instructional videos and sets of problems, the present research assesses the reliability of an algorithms. The method provides a way to optimize educational networking by linking individuals who are looking for and dissemination data regarding certain themes. It represents socially learning networking as a consequence of their understanding searching and expertise propagating preferences between subjects being taught. The technique to examine the social educational networks as it appears in a MOOC forum for discussions that includes lecture videos and assignments for homework. A relatively sparse networks with few attendees of conversations and a constrained selection of subjects as a gauge of the extent to which information searchers and information propagators have connections in the framework. Because very few links can be formed in a highly sparse system, optimization can only produce modest advantages. The creation of a social learning network evaluation measure would give teachers and scholars a way to enhance social learning opportunities in virtual educational settings. The possible uses of self-optimizing communities for aiding collaborative education online is the topic of the final installment of the study.

[20] Learners are given a job to do throughout a course as part of the SCE that is a scenario-based formative assessment method. The missions contain a variety of conditions drawn from actual world situations. Learning how to operate like an expert in a particular field is one of this method's objectives. Though the evaluation's content, psychological, educational and task-developmental components have been extensively studied, there aren't many analytical techniques that enable us to offer students constructive criticism. The goal of this research is to present an outline for a learning analytical approach that consists of three parts: (1) evaluating designing utilizing ECD) (2) a technique for mining data utilizing networking analysis; and (3) a technique for analysis applying a Bayesian network. Employing a computerized statistical system, this analytical approach can evaluate the student's accomplishments. The objectives of the exercises were to assess current educational abilities. A total of 250 samples of the system-collected information were examined. The learning route throughout a course is determined by the findings of a social media research. Additionally, over a number of time periods, the Bayesian network was used to infer every student's current instructional abilities. As a result, the learning analytics suggested in this study can provide efficient learning evaluations and student educational advancement.

Herdetou et al. [21] investigated about the PLA technique. An academic breakthrough called PLA has an opportunity to improve teaching methods and support the achievement of students. However, the level of PLA acceptance among educational settings is still rather low, and educators that employ PLA do not approach it systematically. 11 comprehensive conversations were performed with college instructors and looked at how they interacted with PLA throughout the length of a 37-week graduate course, guided by the UTAUT (a) which variables predict how much PLA is used in teaching practice and (b) what effect a measure — delivering notifications via email to instructors — has on encouraging regular PLA participation. Results revealed that requirements for commitment requirements for effort, and social pressure were some of the elements promoting involvement with PLA. Achievement expectations, good circumstances connected to training, and an absence of comprehension of forecasting information were some of the elements preventing PLA involvement. The effects of using and adopting PLA in educational institutions are examined.

Since the previous two decades, LA and EDM have been used. As the EDM turns the information into useful actions that encourage and strengthen the learning, LA is a human-led process that forecasts student achievement as well as identifies possible challenging aspects of the learner. These methods are utilized by Vaidya and Saini for educational platforms in writing [22]. These techniques are seldom employed in classroom instruction. Educational analytic platforms are utilized to gather information about students, teachers, and courses, but they are incapable to provide reports that those in education would find useful and insightful. The methodology for using LA and EDM practices in a directly educational setting was developed in the work. The model made use of information from the test or learning activity utilized for evaluations, as well as the pupil's continually assessed marks. Numerous procedures are using it to produce results.

Kausar et al. [23] stated that pupils' learning habits have changed as a result of the latest advances in technology, which have also given schooling a fresh impetus. It is simple to assert that advances in technology enable kids to study more successfully, productively. Scholars have been interested in SL, a term that describes learning strategies in the age of technology but is not a new idea. With the support of research-validated models from SLA, learners of all ages may take use of a wide range of materials and sophisticated technologies. It seeks to encourage pupils to have a thorough understanding of the information, which raises levels of accomplishment. Redesigning the core components of conventional school systems will enable the shift of instruction to smart learning. Pupils can therefore learn the data they need, but increasingly additional considerations are required to facilitate learning in an actual-life environment. Context-aware smart everywhere education has replaced online dumb education. In the present investigation, the SLA collection was examined, and for the categorization job, sophisticated collective methods were used. The predictive power of Bagging Tree and Stacking classification is 79% and 78%, correspondingly, outperforming other traditional approaches.

3. PROBLEM STATEMENT

The improvement of student learning outcomes, direction of their development, and facilitation of their participation in the learning process are all impacted significantly by educational feedback. However, there are several difficulties in comprehending the dynamics of educational feedback networks and using their potential for improved learning analytics and feedback mechanisms. The majority of learning analytics research to date has concentrated on discrete feedback occurrences or specific facets of the feedback process, frequently ignoring the intricate relationships and temporal dependencies that exist within educational feedback networks. It is limited in the knowledge of the underlying patterns and structures that underlie effective feedback because traditional analytic methods do not adequately capture the holistic picture of feedback interactions among students, instructors, and educational resources. Furthermore, while improvements in artificial intelligence and machine learning have opened the path for personalized suggestions and predictive modelling, their use in educational feedback networks is still unexplored. For capturing the complex dynamics of feedback across time, identifying significant nodes, and forecasting future feedback patterns, the combination of graph theory with LSTM-based modelling has a lot of potential [24].

4. METHODOLOGY

In order to better understand educational feedback networks and improve learning analytics and personalized feedback mechanisms, this study uses an approach that blends graph theory with LSTM based modelling. The study makes use of a sizable dataset made up of educational exchanges from various learning environments, including student contributions, assessments, and teacher comments. A network model is created using graph theory in which the nodes stand in for the students, teachers, and educational resources, and the edges indicate the links between these. LSTM-based models also record the temporal connections in the feedback networks. This technique might improve teaching strategies by combining graph theory with LSTM-based modelling. Figure 2 illustrates the methodology.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

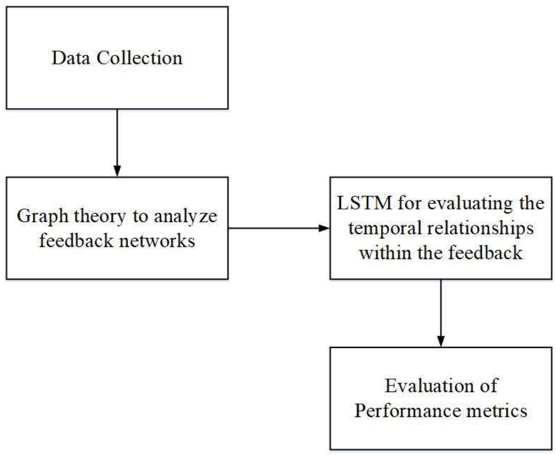

Figure 2: Proposed Graph theory-LSTM

4.1 Data Collection

The technique was created over the course of three different information collecting cycles using recordings of pupils working in teams to solve challenges. To keep track of the talks in the initial repetition, qualitative notes and memos were prepared as assessments were being made. The notes also contained some talk-turn statistics. In the following repetition, hand-drawn sketches were used to record people's relative physical locations within every group. Every talk-turn among the two individuals was represented by a line, and tally marks were used to record the quantity of talk-turns. As a consequence of this, the information that is used for the graph theory computations was unsupervised. The third and final iteration integrated the results of the first two iterations and additionally documented the talk-turn order. Along with the physically shown schematics, talk-turn information was collected in a database using a question-and-answer style, and qualitative notes and memos were created while conducting the interviews. According to the sequence in which every individual spoke for the first time in the discussion, an identification was given to that member. Directed information to help with graph theory computations by recording each participant's identity under a combination of a query or respond category every time they spoke.

4.2 Graph theory

In order to examine the dynamics of educational feedback networks, graph theory is used. Since the sequence in how pupils speak in the group is considered as a substitute for the structure of the conversation, the theory of graphs to simulate that order. A collection of mathematical equations and ideas are used in graph theory to analyze interactions between different things of concern. A graph's basic components are its nodes and edges. Edges show the relationships among nodes, which serve in for the items of concern. The collective's members are modelled as nodes using the technique. A talk-turn is what people refer to as an edge that connects two participants when they speak one afterwards another. Edges can be interpreted in a variety of ways. They may observe how the conversation shifts from one person to the next, who is prepared to speak following other people, and who offers suggestions that might be developed or addressed. Although everybody in the team might be watching while an individual speaks, an edge does not always indicate that two people should speak to one another immediately. Actually, just one individual may speak during the following round. An edge therefore simply denotes that one speaker spoke after another.

Edges include extra crucial characteristics. Edges may initially be weighed, generally according to the current rate. The amount of talk-turns among any two individuals is captured using edge weight, which represents the amount of occasions a single individual speaks after another individual has spoken. Edges can be guided or undirected, second. With the approach, individuals' conversations are tracked via the edges of a directed graph. Although a directed network allows us to measure the reciprocating among two nodes that is, if one reacts more quickly after another reacts but the opposite is true around, it is chosen over a graph that is not directed. An undirected graph, on the contrary, just reveals the fact there occurred a talk-turn among the two nodes. Recognizing the equal treatment and diversity of various pupils in group educational settings necessitates monitoring the directional nature of discussions.

Graphs may have a wide variety of mathematical characteristics, and those that would best depict the changing dynamics of group conversations is chosen. Degrees and density are connected factors that have to do with the amount of links there are between nodes; in this case, these metrics describe the amount of individuals who speak after someone else. The degree variable of every single node counts the edges that connect it to other nodes. The aggregate amount of connections in a graph, normalized to the highest number of edges feasible, is the density, an attribute for every graph. The density for a certain graph is determined as follows and has a value range of 0 to 1.

$$Density = \frac{No.of\ edges}{Maximum\ no.of\ possible\ edges} \quad (1)$$

Individuals who participate in talk-turns either alone or among more individuals are indicated by nodes with greater degrees. The general diversity of individuals' discussing after others is larger in graphs having higher density levels; in the sense that individuals engage in conversation following various individuals more frequently.

A further set of associated features for both each node and the whole network are centrality and centralization. The idea that certain nodes in a graph are of greater importance to the interconnections of edges that others is captured by the concept of centrality. Several techniques that emphasize various interpretations concerning what an edge in a network implies may be used to assess centrality. A variety of kinds of centrality focus on interconnections between edges that extend above two nodes and were frequently employing to analyze the data that flow among numerous individuals. Since everybody in the team may be attending to the data, it does not suggest that data is merely moving from one person to another in the present investigation. Instead, talk-turns among the two individuals as the simplest kind of assessment. As a result, the degree of centrality is the measure that is most suitable since it only considers a node's degrees or the amount of edges that relate it to other nodes. For an individual node, degree centrality is determined as,

Degree Centrality = No. edges pointed to a node + No. edges pointed out of a node (2)

A further indication of active engagement is when a node has an elevated level of centrality, which indicates that an individual speaks both prior to and following a variety of people. This setting offers extra details on the talk-turn rate.

Although centrality is a metric for each and every node, centralization assesses when the whole network is centered about a single node. According to this, a degree centralization is employed since there are never any edges between more than two nodes.

A particular graph's degrees centralization, which spans from 0 to 1, is determined as,

*Centralization = No. of nodes * Maximum degree of any node -* $\sum degree\ centralities$ (3)

A degree centralized to assess the degree to which the most active member dominates a debate. Sub graphs are scaled-down versions of larger graphs. Analyzing the edges and their respective weights, a sub graphs to identify strongly linked subgroups inside the overall participation group. High connectivity suggests that members of the subgroups speak more often after each other compared after members of the outer grouping. Individuals in the subgroups might have been more inclined to speak following another person speaks or be more inclined to share ideas which can be elaborated upon or addressed.

4.3 Long Short Term Memory

Analyzing the dynamics of educational feedback networks requires the use of LSTM-based models. Given the sequential nature of educational experiences, LSTM-based models were created with the explicit purpose of capturing and displaying the temporal correlations that exist within these feedback networks. It is possible to assess the feedback's quality, pinpoint influential nodes, and forecast upcoming feedback patterns by including LSTM models into the study. A deeper understanding of the intricate dynamics of educational feedback networks is possible thanks to the use of LSTM models, which allow for the analysis of temporal relationships and patterns in the data. As a result, LSTM-based modelling improves the capacity to draw insightful conclusions from the information and helps to advance learning analytics and feedback systems in education.

The four basic constituents of an LSTM network are a memory unit d, a forget gate g, an input gate j, and an output gate i. The subsequent formulae represent the structure of the system as an expression of time t. The sigmoid function σ is used here.

$$j_t = \sigma\left(V_{yj}y_t + V_{kj}k_{t-1} + c_j\right) \quad (4)$$

$$g_t = \sigma\left(V_{yg}y_t + V_{kg}k_{t-1} + c_g\right) \quad (5)$$

$$i_t = \sigma\left(V_{yi}y_t + V_{ki}k_{t-1} + c_i\right) \quad (6)$$

$$d_t = g_t d_{t-1} + j_t tank\left(V_{yd}y_t + V_{kd}k_{t-1} + c_d\right) \quad (7)$$

When doing action recognition, the input y_t is frequently a posture representations or the result of a CNN trained for frame-by-frame action detection. The LSTM layer's output k is computed as follows:

$$k_t = i_t tank(d_t) \quad (8)$$

The y_t of a layer may differ from the k_t of the layer before it when numerous layers are linked after

Journal of Theoretical and Applied Information Technology
15th January 2024. Vol.102. No 1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

one another. The structure of the network is chained and copied as an LSTM is taught by removing it over time. The parameters that can be trained V and c are able to be updated over time via variations.

5. RESULT AND DISCUSSIONS

5.1 Accuracy

Accuracy is used to evaluate the system model's overall performance. It basically holds that every experience can be anticipated with accuracy. Eqn (9) offers accuracy,

$$Accuracy = \frac{T_{Pos} + T_{Neg}}{T_{Pos} + T_{Neg} + F_{Pos} + F_{Neg}} \quad (9)$$

Table 1: Comparison of accuracy

Methods	Accuracy (%)
RF [25]	50.4
SVM [25]	41.2
LSTM [25]	64.8
Graph theory - LSTM	98.12

Table 1 compares the accuracy of proposed graph theory-LSTM with other existing methods like RF, SVM, and LSTM. The proposed graph-theory has an accuracy of about 98.12% which is higher than the other methods. It is shown in Figure 3.

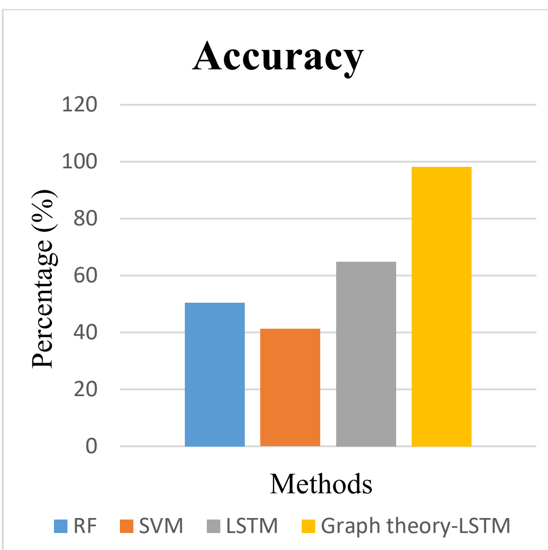

Figure 3: Comparison of accuracy

5.2 Precision

Precision also describes how closely two or more calculations resemble one another in addition to being correct. The connection between precision and accuracy shows how consistently an observation may be made. It is possible to utilize Eqn (10), which computes precision.

$$P = \frac{T_{Pos}}{T_{Pos} + F_{Pos}} \quad (10)$$

Table 2: Comparison of precision

Methods	Precision (%)
RF [25]	52.2
SVM [25]	44.1
LSTM [25]	63.9
Graph theory - LSTM	97.34

The precision of proposed graph theory-LSTM is compared with the precision of existing methods in table 2 and the proposed graph theory-LSTM method is found to be more efficient than the other methods. It is depicted in Figure 4.

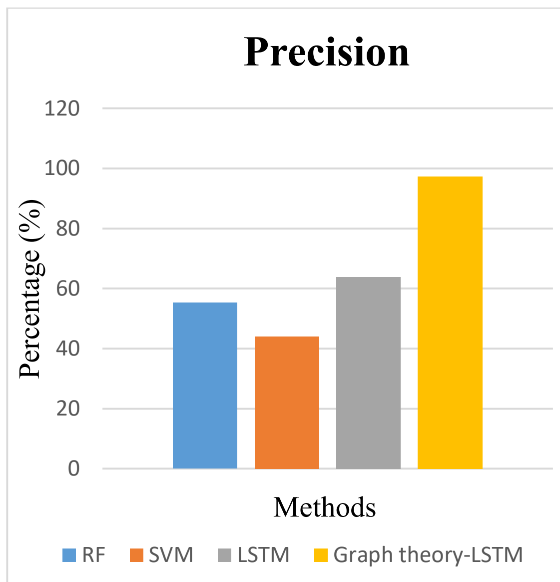

Figure 4: Comparison of precision

5.3 Recall

The percentage of all relevant results that the algorithms accurately sorted is known as recall. The suitable positive for these numbers is calculated using the ratio between the true positive and false negative values. In Eqn (11) it is mentioned.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

$$R = \frac{T_{Pos}}{T_{Pos} + F_{Neg}} \quad (11)$$

Table 3: Comparison of recall

Methods	Recall (%)
RF [25]	51
SVM [25]	39.3
LSTM [25]	65.1
Graph theory - LSTM	93.4

The recall of the proposed graph theory-LSTM method is compared with the recall of methods like RF, SVM, and LSTM in table 3. The recall of the proposed graph theory-LSTM is 93.4%. Figure 5 represents this.

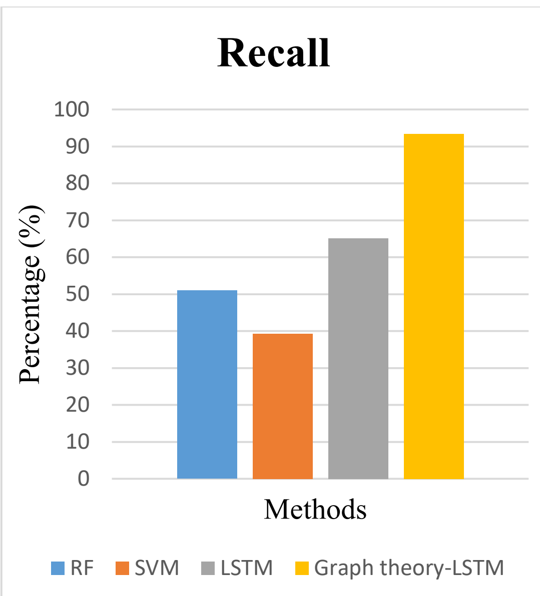

Figure 5: Comparison of recall

5.4 F1-Score

Accuracy and recall are combined in the F1-Score calculation. The F1-Score in Eqn (12) is determined using precision and recall.

$$F1 - score = \frac{2 \times precision \times recall}{precision + rec} \quad (12)$$

Table 4: Comparison of F1-Score

Methods	F1-Score (%)
RF [25]	51
SVM [25]	35.4
LSTM [25]	63.7
Graph theory - LSTM	94.35

Table 4 compares the F1-score of the proposed graph theory-LSTM with the F1-score of the other existing methods and found that the proposed graph theory-LSTM has highest F1-score of about 94.35%. It is shown in figure 6.

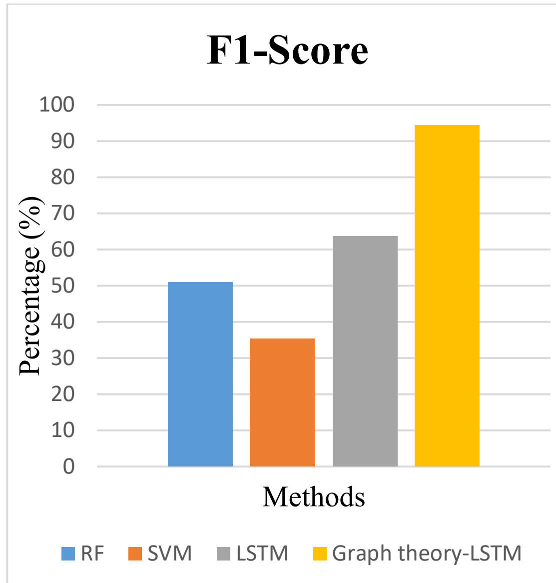

Figure 6: Comparison of F1-Score

5.5 Discussion

The overall discussion reveals the efficacy of the proposed method, which combines graph theory and LSTM-based modeling, in exploring the dynamics of educational feedback networks. The comparison of methods highlights the substantial improvements achieved by the novel approach in terms of accuracy. Specifically, the results indicate that the Graph Theory - LSTM method outperforms other established techniques, including Random Forest (RF) at 50.4%, Support Vector Machine (SVM) at 41.2%, and standalone LSTM at 64.8%. The remarkable accuracy of 98.12% achieved by the proposed method underscores its potential for enhanced learning analytics and feedback mechanisms in educational settings.

While the findings demonstrate the superiority of the Graph Theory - LSTM approach, it is essential to acknowledge certain limitations within the scope of this work. Firstly, the study may be subject to dataset-specific nuances, and the generalizability of the proposed method to diverse educational contexts needs further exploration. Additionally, the

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

computational demands of the integrated model may pose challenges in real-time applications or resource-constrained environments. Future research efforts should aim to address these limitations, ensuring the scalability and robustness of the proposed methodology across varied educational scenarios. Nevertheless, the present work marks a significant advancement in the field, laying the groundwork for more effective and nuanced learning analytics and feedback mechanisms in educational systems.

6. CONCLUSION

The present research delves into the transformative potential of learning analytics and customized feedback systems in reshaping education. Employing a robust dataset encompassing diverse educational interactions, the study leverages the synergies between graph theory and LSTM-based models to analyze the dynamics of educational feedback networks comprehensively. The graph theory-based network model facilitates a holistic understanding of the educational environment, while LSTM models, attuned to sequential structures, capture temporal correlations within feedback networks. This integration enables the assessment of input quality, identification of significant nodes, and prediction of future feedback patterns. However, it is crucial to acknowledge a limitation inherent in the study. While the proposed paradigm offers a novel perspective on evaluating educational feedback networks, the generalizability of findings may be influenced by the specifics of the dataset used. Variability in educational contexts and diverse student populations could impact the applicability of the developed model. Future research endeavors should thus focus on validating the proposed approach across a wider range of educational scenarios to ensure its robustness and effectiveness in diverse settings. Despite this limitation, the integration of graph theory and LSTM-based models presents a promising avenue for advancing educational practices, informing instructional design decisions, and supporting student achievement.

REFERENCE

[1] "Adaptive learning objects in the context of eco-connectivist communities using learning analytics - ScienceDirect." https://www.sciencedirect.com/science/article/pii/S2405844019363820 (accessed Jun. 20, 2023).

[2] M. Ding, K. Yang, D.-Y. Yeung, and T.-C. Pong, "Effective Feature Learning with Unsupervised Learning for Improving the Predictive Models in Massive Open Online Courses," in *Proceedings of the 9th International Conference on Learning Analytics & Knowledge*, in LAK19. New York, NY, USA: Association for Computing Machinery, Mar. 2019, pp. 135–144. doi: 10.1145/3303772.3303795.

[3] "Effective Feature Learning with Unsupervised Learning for Improving the Predictive Models in Massive Open Online Courses | Proceedings of the 9th International Conference on Learning Analytics & Knowledge." https://dl.acm.org/doi/abs/10.1145/3303772.3303795 (accessed Jun. 20, 2023).

[4] D. Gasevic, Y.-S. Tsai, S. Dawson, and A. Pardo, "How do we start? An approach to learning analytics adoption in higher education," *The International Journal of Information and Learning Technology*, vol. 36, no. 4, pp. 342–353, Jan. 2019, doi: 10.1108/IJILT-02-2019-0024.

[5] S. K. Banihashem, K. Aliabadi, S. Pourroostaei Ardakani, M. R. Nili AhmadAbadi, and A. Delavar, "Investigation on the Role of Learning Theory in Learning Analytics," *Interdisciplinary Journal of Virtual Learning in Medical Sciences*, vol. 10, no. 4, pp. 14–27, Dec. 2019, doi: 10.30476/ijvlms.2019.84294.1001.

[6] "Learning Analytics to Support Teachers' Assessment of Problem Solving: A Novel Application for Machine Learning and Graph Algorithms | SpringerLink." https://link.springer.com/chapter/10.1007/978-3-319-64792-0_11 (accessed Jun. 20, 2023).

[7] A. F. Wise, "Learning Analytics: Using Data-Informed Decision-Making to Improve Teaching and Learning," in *Contemporary Technologies in Education: Maximizing Student Engagement, Motivation, and Learning*, O. O. Adesope and A. G. Rud, Eds., Cham: Springer International Publishing, 2019, pp. 119–143. doi: 10.1007/978-3-319-89680-9_7.

[8] O. Noroozi, I. Alikhani, S. Järvelä, P. A. Kirschner, I. Juuso, and T. Seppänen, "Multimodal data to design visual learning analytics for understanding regulation of learning," *Computers in Human Behavior*, vol. 100, pp. 298–304, Nov. 2019, doi: 10.1016/j.chb.2018.12.019.

[9] "Sustainability | Free Full-Text | Predicting At-Risk Students Using Clickstream Data in the Virtual Learning Environment."

https://www.mdpi.com/2071-1050/11/24/7238 (accessed Jun. 20, 2023).

[10] "Using learning analytics to develop early-warning system for at-risk students | SpringerLink." https://link.springer.com/article/10.1186/s41239-019-0172-z (accessed Jun. 20, 2023).

[11] W. Xing, B. Pei, S. Li, G. Chen, and C. Xie, "Using learning analytics to support students' engineering design: the angle of prediction," *Interactive Learning Environments*, vol. 0, no. 0, pp. 1–18, Oct. 2019, doi: 10.1080/10494820.2019.1680391.

[12] "Virtual learning environment to predict withdrawal by leveraging deep learning - Hassan - 2019 - International Journal of Intelligent Systems - Wiley Online Library." https://onlinelibrary.wiley.com/doi/abs/10.1002/int.22129 (accessed Jun. 20, 2023).

[13] A. A. Mubarak, H. Cao, and S. A. M. Ahmed, "Predictive learning analytics using deep learning model in MOOCs' courses videos," *Educ Inf Technol*, vol. 26, no. 1, pp. 371–392, Jan. 2021, doi: 10.1007/s10639-020-10273-6.

[14] F. Chen and Y. Cui, "Utilizing Student Time Series Behaviour in Learning Management Systems for Early Prediction of Course Performance," *Journal of Learning Analytics*, vol. 7, no. 2, pp. 1–17, 2020.

[15] H. Yan, F. Lin, and Kinshuk, "Including Learning Analytics in the Loop of Self-Paced Online Course Learning Design," *Int J Artif Intell Educ*, vol. 31, no. 4, pp. 878–895, Dec. 2021, doi: 10.1007/s40593-020-00225-z.

[16] C. Huang, Z. Han, M. Li, X. Wang, and W. Zhao, "Sentiment evolution with interaction levels in blended learning environments: Using learning analytics and epistemic network analysis," *Australasian Journal of Educational Technology*, vol. 37, no. 2, Art. no. 2, May 2021, doi: 10.14742/ajet.6749.

[17] A. S. Aljaloud *et al.*, "A Deep Learning Model to Predict Student Learning Outcomes in LMS Using CNN and LSTM," *IEEE Access*, vol. 10, pp. 85255–85265, 2022, doi: 10.1109/ACCESS.2022.3196784.

[18] Y. Dyulicheva and B. E., *Learning Analytics of MOOCs based on Natural Language Processing*. 2021.

[19] T. Doleck, D. J. Lemay, and C. G. Brinton, "Evaluating the efficiency of social learning networks: Perspectives for harnessing learning analytics to improve discussions," *Computers & Education*, vol. 164, p. 104124, Apr. 2021, doi: 10.1016/j.compedu.2021.104124.

[20] Y. Choi and Y. I. Cho, "Learning Analytics Using Social Network Analysis and Bayesian Network Analysis in Sustainable Computer-Based Formative Assessment System," *Sustainability*, vol. 12, no. 19, Art. no. 19, Jan. 2020, doi: 10.3390/su12197950.

[21] C. Herodotou, C. Maguire, N. McDowell, M. Hlosta, and A. Boroowa, "The engagement of university teachers with predictive learning analytics," *Computers & Education*, vol. 173, p. 104285, Nov. 2021, doi: 10.1016/j.compedu.2021.104285.

[22] A. Vaidya and J. R. Saini, "A Framework for Implementation of Learning Analytics and Educational Data Mining in Traditional Learning Environment," in *ICT Analysis and Applications*, S. Fong, N. Dey, and A. Joshi, Eds., in Lecture Notes in Networks and Systems. Singapore: Springer, 2021, pp. 105–114. doi: 10.1007/978-981-15-8354-4_11.

[23] S. Kausar *et al.*, "Mining Smart Learning Analytics Data Using Ensemble Classifiers," *Int. J. Emerg. Technol. Learn.*, vol. 15, no. 12, p. 81, Jun. 2020, doi: 10.3991/ijet.v15i12.13455.

[24] "Learning analytics in higher education: a preponderance of analytics but very little learning? | SpringerLink." https://link.springer.com/article/10.1186/s41239-021-00258-x (accessed Jun. 20, 2023).

[25] B. Akram, W. Min, and E. Wiebe, "Improving Stealth Assessment in Game-based Learning with LSTM-based Analytics".