JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

OPTIMIZING ACADEMIC FEEDBACK SYSTEMS THROUGH BUSINESS INTELLIGENCE: A STRATEGIC APPROACH TO ENHANCING UNIVERSITY RANKINGS IN INDIAN HIGHER EDUCATION INSTITUTIONS

Hemant S Sharma 1* and Dr. Hiren D Joshi 2
1 Ph.D. Scholar, Department of Computer Science, Gujarat University, Ahmedabad, Gujarat, India
***Corresponding author: hemantsharma@gujaratuniversity.ac.in**

2 Professors, Department of Computer Science, Gujarat University, Ahmedabad, Gujarat, India
Guide: hdjoshi@gujaratuniversity.ac.in

Abstract: University ranking systems significantly impact institutional reputations and assist students in making informed decisions. Conventional ranking methodologies use subjective surveys and criteria, resulting in a deficiency of transparency and consistency. Recent studies have used machine learning models such as LSTMs, BiLSTMs, and TCNs to classify tertiary institutions into tiers; nevertheless, these algorithms encounter difficulties in distinguishing closely ranked institutions, particularly Tier-1 and Tier-2. Contemporary ranking algorithms exhibit data security and traceability deficiencies, prompting apprehensions over potential institutional manipulation and prejudice. A unique blockchain-based Hybrid TCN+BiLSTM model enhances academic feedback systems and university rankings in Indian higher education institutions. Temporal Convolutional Networks (TCN) and Bidirectional Long Short-Term Memory (BiLSTM) enhance classification precision and the modeling of long-range dependencies. Based on observation or experience rather than theory or pure logic. The Hybrid TCN+BiLSTM model surpasses conventional deep learning methods, achieving an accuracy, precision, recall, and F1-score of 92.73%. The ROC curve study demonstrates its efficacy in hierarchical classification, especially in Tier-4 predictions. Besides classification accuracy, blockchain technology ensures data immutability, verifiability, and transparency, hence mitigating biases in institution rankings. Business intelligence in academic assessment may be directed by the focus on explainability in AI-driven ranking algorithms. This research develops a scalable and robust framework for university ranking systems, facilitating real-time data streams, ensemble learning, and specialized ranking metrics.

Keywords: ***Higher Education Ranking, College Tier Classification, Hybrid TCN+BiLSTM, Temporal Convolutional Networks, Bidirectional Long Short-Term Memory.***

I.INTRODUCTION

Indian universities are competing to enhance academic ranking and performance at both local and global levels. Rankings such as India's National Institutional Ranking Framework (NIRF) are crucial for the university's reputation, teacher and student recruitment, and public and private investments (Gupta et al., 2025). Research output, faculty quality, student satisfaction, and industry interaction are all taken into account while NIRF rankings are made. Institutions must decipher and interpret such rankings to identify their areas of excellence and scope for improvement(Henderson et al., 2019).

Peer reviews, focus groups, formal interviews, and hand-written questionnaires have all been utilized by universities in the past to gather feedback from students and instructors. Although effective, these processes are defective because they have low customization, are subjective, biased, subject to delayed analysis, have disparate data, and lack predictive data (Dabhade et al., 2021). The qualitative feedback used in traditional feedback collection is more likely to be influenced by personal experiences, biases, and personal opinions as opposed to scholastic achievements. The identification and utilization of improvements are delayed by the time-consuming human elicitation, processing, and analysis of feedback. Substantive feedback information is found in survey responses, written comments, and institution records but can be challenging to collect and analyze. Old ways put more weight on the rearview than on forecasts geared toward enriching institutional learning and policy. Rather than specific suggestions for students, teachers, or departments, feedback analysis tends to yield general conclusions. These challenges mandate the development of data-driven, AI-based feedback systems that provide personalized, predictive, and real-time information to enable academic attainment and institution ranking. For classifying colleges according to NIRF rankings, the present study proposes a sophisticated hybrid machine learning method that integrates Bidirectional Long Short-Term Memory (BiLSTM) with Temporal Convolutional Networks (TCN).(Zhang & Chu, 2024)(Wang, 2023).

TCN, a deep learning convolutional algorithm, is computationally efficient and capable of extracting long-range relations in ranking series(Hu, 2024). It can produce insights, detecting trends, and analyzing institutional ranking-related information. (Singla et al., 2022)BiLSTM, a form of LSTM that takes both past and future contexts into consideration, improves the classification process by detecting patterns within ranking sequences, grasping subtle dependencies, and classifying institutions into various NIRF ranking grades in terms of their research performance, faculty quality, and student satisfaction(Chen, 2024). To determine patterns and trends in institutional performance, recruitment of faculty, and accreditation compliance, TCN can process rank-structured information. TCN is more appropriate for sequential tabular data models than regular machine learning models like random forests and gradient boosting, making it suitable for monitoring changes in rankings over time.Using the integration of TCN and BiLSTM(Gopali et al., 2021), the system can now extract information from qualitative and ranking measures, giving the universities real-time analytics to enhance rankings as well as academic quality.

The goal of this study is to create a categorization system based on artificial intelligence. that uses NIRF rankings to classify Indian universities. The key goals of this study are to optimize structured ranking analysis using TCN for enabling advanced pattern identification and trend prediction, improve qualitative feedback analysis using BiLSTM-based NLP techniques to extract meaningful insights from text-based answers, and integrate AI-driven approaches for assisting universities in improving their ranking performance. This study aims to optimize ranking analysis by employing the hybrid TCN + BiLSTM model, thus enabling data-driven reform in Indian higher education systems(Feng et al., 2024).

II. LITERATURE REVIEW

S.no	Topic	Journal / Conference	Data Collection / Sample Size	Methodology	Findings	Research Gap / Limitation
(Cardoso & Su, 2022)	Designing a Business Intelligence and Analytics Maturity Model for Higher Education: A Design Science Approach	MDPI	Two seminars with practitioners from more than 10 countries and three case studies involving universities from different nations	Design Science Research (DSR) incorporate literature review, iterative design and development, self-assessment, workshops, and feedback evaluation.	HE institutions can assess BIA maturity using the HE-BIA maturity model. Self-assessment allows institutions to understand their BIA landscape and discuss it. Case studies and seminars guided model updates.	Ambiguous terminology needed to be clarified. User feedback prompted alterations in Cloud Computing. The research was undertaken before the COVID-19 pandemic; results may differ
(Amato et al., 2023)	AI-Powered Learning: Personalizing Education for each Student	Ceur-ws.org	Four European universities' Master's Program Human-Centred AI and includes a University of Naples Federico II case study. Case studies and research with industry partners and stakeholders use Deep Fake AI MOOC lessons.	It proposes an HCAIM consortium exemplar curriculum for AI ethics in education. The initiative promotes cross-disciplinary computer science, social sciences, and humanities education, Erasmus student exchange, and industry-academia AI application development.	AI-based MOOCs enable personalized, effective, and accessible learning. The Human-Centred AI Master's Programme (HCAIM) emphasises universities' ethical, equitable, and responsible AI use. All students enjoy a responsive and adaptive AI curriculum, and industry-academia symbiosis is needed to keep AI education relevant.	Ethics like bias and misinformation in AI-generated learning content and empirical data on AI-based MOOC long-term success are examined in the study. The study finds program implementation heterogeneity in university traditions, resources, legal frameworks, and regulatory issues in complying without undermining AI-based education's innovative and productive nature.
(Pallathadka et al., 2023)	Classification and prediction of student performance data using various machine learning algorithms	Researchgate.net	Study uses 33 attributes and 649 instances from Student performance data from UCI Machinery.	The study predicts student performance using machine learning techniques like SVM, ID3, C4.5, and Naïve Bayes.	The analysis shows that student talents and interests affect performance, helping educators identify struggling students. Educational data mining improves instruction, faculty	The study uses past academic performance without considering socio-economic, political, or learning style variables that may affect student performance. This

				Several algorithms classify the dataset after quality pre-processing.	performance, and question paper difficulty, the study shows. In tested algorithms, SVM best classifies student performance.	study found that SVM worked best, but hybrid and deep learning were not tested. Personalized learning with predictive advising may be worth investigating.
(Khan et al., 2021)	Educational Blockchain: A Secure Degree Attestation and Verification Traceability Architecture for Higher Education Commission	MDPI	No dataset is specified, but blockchain nodes and smart contracts validate it. The cross-chain platform enables institutions, federal authorities, and regional offices to participate.	Securely verifies and tracks degrees with Hyperledger Fabric. Record-keeping offices and institutions need two peer nodes for a distributed ledger. Only consensus is verified by Apache Kafka ordering service. REST API loads and modifies degree records, while smart contracts verify them. Digital signatures, hash encryption, and permissioned network interfaces secure the system.	HEDU-Ledger certifies degrees decentralized and securely on blockchain. Immutability, security, and transparency are guaranteed by smart contracts and digital signatures. Replaces manual processes, speeds verification, and improves data privacy and integrity. It prevents fraud, cyberattacks, and unauthorized changes. Distributed ledgers support non-repudiation, traceability, and efficient storage.	Cross-chain platform integration is difficult because blockchain solutions are not interoperable between institutions, according to the study. Automation is needed to reduce manual data entry. Large-scale blockchain implementation in HEC is hindered by unclear legal and regulatory frameworks. To improve performance and lower transaction costs, private blockchain networks must optimize storage and scalability.
(Shaik et al., 2023)	Sentiment analysis and opinion mining on educational data: A survey	Science Direct	Systematic questionnaire for student and faculty evaluations; 66,000 student assessments (MOOCs); six Moodle datasets; annotated datasets for artificial intelligence models.	Document, sentence, entity, and aspect sentiment analysis. AI-based methods (ML, DL, transformers). Lexikon-based and corpus-based sentiment annotation, topic modeling, and reinforcement learning for sentiment-driven conversational agents. Random Forest, LSTM, SVM, ANN ML models.	Faculty evaluation accuracy was 98.87% with Random Forest. LSTM with GloVe classified MOOC sentiment 95.80% accurately. Educational decision support with Aspect2Labels (A2L) framework was 91.3% accurate. Educational sentiment analysis yielded 97% and 93% for SVM and ANN. AI-powered chatbots improved cognition and engagement.	Multi-polarity, negation, and opinion spam detection issues. Finer NLP techniques like topic modeling are needed for better insights, but AI-based methods dominate. Real-time and multilingual sentiment adaptation are understudied.
(Kastrati et al.,	Sentiment Analysis of Students’	MDPI	The 612 studies were reduced to 92 relevant	PRISMA-based structured mapping review.	Deep learning has boosted sentiment analysis in education.	Unstructured datasets, small dataset sizes, and

2021)	Feedback with NLP and Deep Learning: A Systematic Mapping Study		ones. Small datasets (≤5000 samples) typically impacted result reliability. Many datasets were private.	The study used a stepwise selection process (research questions, keywords, inclusion/exclusion criteria, data extraction, and analysis). The review examined NLP, ML, and DL sentiment analysis in education.	Dataset structuring, emotional expression detection, standardization, and evaluation metric improvements are crucial. It was stressed that sentiment analysis requires contextualization and conceptualization.	non-public availability hinder reproducibility. Little emphasis on emotion detection and context. Evaluation metrics vary and lack standardization hinder comparative analysis. The study was limited to English papers and may have been missing due to database indexing issues.
(Balaji, 2024)	HOW TO INCREASE UNIVERSITY WORLD RANKING: A CASE STUDY	International Journal of Library and Information Science (IJLIS)	Data gathered in August 2024 from multiple ranking sources. Analysis conducted on six Indian agricultural universities. The Ranking Web comprises 32,000 institutions from over 200 countries.	Assesses universities using webometric and bibliometric indicators. Assesses research, teaching, international collaboration, infrastructure, innovation, reputation, inclusivity, and employability. Ranking scientific publications by visibility, impact, and accessibility.	Indian universities rank low in the world due to low access, faculty deficit, outdated curriculum, and infrastructural inadequacies. Universities must serve both international and local needs. Reputation is the secret to branding higher education. Global rankings place IISc Bengaluru and IIT Bombay as number one in India.	Current ranking frameworks emphasize web presence and open-access initiatives but may not capture education quality or social impact. Indian universities need a plan to improve global rankings using inclusivity, outcome-based metrics, and transparency.
(Kumar et al., 2021)	NIRF India Rankings 2020 Analyzing the Ranking Parameters and Score of Top 100 Universities	Researchgate	The official NIRF website provided the data. research examined the leading 100 universities according to the NIRF India Ranking 2020.	Descriptive cross-sectional research. SPSS-21/Excel analysis. Perception, Outreach & Inclusivity, Graduation Outcomes, Teaching, Learning & Resources, and Research & Professional Practice were ranking factors. We used regression and correlation.	Ranking is strongly correlated with RP and PR ($R^2 = 0.746$). TLR and OI barely affect ranking. GO has a weak correlation with total score ($R^2 = 0.37$). Universities with more research and citations rank higher. Library spending boosts research output and ranking. Government-funded universities dominate the top 100.	Study only covers top 100 universities, limiting generalization. External socioeconomic and funding factors were ignored. No analysis examined faculty quality and international collaboration.

(Hmoud et al., 2023)	Factors influencing business intelligence adoption by higher education institutions	ScienceDirect	Data was gathered via a Google Forms-based online survey. 387 people who held managerial roles at Jordanian higher education institutions made up the study population.	The investigation used positivist research and PLS-SEM for data analysis. Arabic and English were used to accurately translate the questionnaire. Validity and reliability were assessed by factor loading, AVE, and CR. A five-point Likert scale measured constructs. Content validity was checked by BI experts.	BI adoption depends on support from upper management, information culture, organizational preparedness, relative benefits, perceived complexity, compatibility, information quality, and vendor choice. Information culture helped adoption most, while complexity hindered it. No competitive pressure was significant.	The study's convenience sampling and Jordanian HEI focus may limit generalizability. The study does not examine BI adoption's long-term effects or resistance factors. Further research should examine contextual factors and longitudinal effects.
(Shaik et al., 2022)	A Review of the Trends and Challenges in Adopting Natural Language Processing Methods for Education Feedback Analysis	Ieee.org	Student feedback survey, questionnaire, and online educational portal data. StackOverflow, GitHub, and job posting and MOOC scrapes are used for domain-specific NLP. Sarcasm detection datasets for short, long, transcripts, and dialogues. Six emotion classes validated emoticons dataset.	NLP for sentiment analysis, entity recognition, text summarization, and topic modeling. Bi-LSTM/CSIT-NER domain-specific NLP models. SVM, LSTM, CNN rule-based, statistical, and deep learning sarcasm detection. Disambiguating word sense with BERT. The Bi-LSTM and CNN models processed emoticons. Sentiment analysis with explicit and implicit extractions. Transfer learning and sampling fix data imbalance.	NLP can improve educational feedback analysis but struggles with sarcasm, ambiguity, and emoticons. AI can improve educational decision-making with deep learning and knowledge graphs. Bi-LSTM, CNN, and BERT are good classification methods for educational NLP.	Training NLP models without domain-specific datasets is difficult. Sarcasm, ambiguity, and emoticons in student feedback are difficult to detect. Student feedback dataset imbalance affects classification performance. Education uses aspect-based sentiment analysis little. Smart tutoring systems with AI for personalized learning are needed.

III. BACKGROUND

Bi-LSTM Network

A Bi-LSTM model comprises The LSTM in this model is a variation of their existing neural network (RNN), and it has two versions: a forward LSTM and a backward LSTM. A gating unit is added to the LSTM in order to address the issue of gradient disappearance in conventional RNN. This gives the LSTM a more crucial capability to record long-term dependencies, while also allowing the RNN to better identify and use the dependencies present in long-distance data.

In LSTM, every cell unit takes on a new structure that is mostly made up of our components: input gate, output gate, forget gate ft, and storage unit ct. Figure 1 depicts the internal organization of a single LSTM module cell.

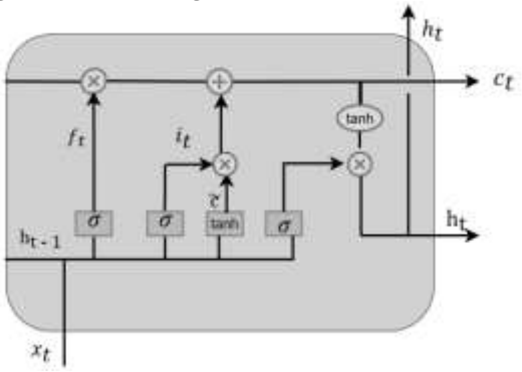

Figure 1:LSTM cell unit

The following is the LSTM update formula.:
Ignore the gate mechanism.

$$f_t = \sigma(W_{(f)}x_t + U_{(f)}h_{t-1} + b_{(f)}) \quad (8)$$

The forgettable gate f_t It is a memory cell for rest. σ symbolizes the activation function of the sigmoid $W_{(f)}$ is a matrix of weights.$x_t$symbolizes the input at one moment. t,U Is the hidden layer output's weight matrix, h_{t-1} reflects the short-term memory and is the concealed state. $b_{(f)}$ the offset vector

Mechanism of the input gate:

$$i_t = \sigma(W_{(i)}x_t + U_{(i)}h_{t-1} + b_{(i)}) \quad (9)$$

The gate of input i_t denotes the Sigmoid activation function, and σ stands for the input gates that regulate the memory cell's input. $W_{(i)}$ is a matrix of weights. x_t symbolizes the input at one moment. U Is the hidden layer's weight matrix output h_{t-1} Is the state concealed? representing the memory that is short-term is $b_{(i)}$ the vector of offset

Three current unit statuses:

$$\tilde{c} = f_t \odot c_{t-1} \, (3) \quad (10)$$

$\tilde{c}$ It is a potential memory cell. The forget gate f_t Is a memory cell reset? c_{t-1} is the condition of the cell of $t-1$ shows the state of the long-term memory 4 update unit.

$$c_t = \tilde{c} + i_t \odot tanh(W_{(c)}x_t + U_{(c)}h_{t-1} + b_{(c)})(11)$$

c_t Does The condition of the cell represent Long-term memory, $\tilde{c}$ Is the memory cell of the candidate i_t W_((c)) is a weight matrix that represents the input gates that regulate the memory cell's input? $x_t$represents one input at a time UIs the hidden layer outputs' weight matrix h_{t-1} Does the short-term memory reflect the hidden state? $b_{(c)}$ Does the offset vector

Five mechanisms of the output gate

$$o_t = \sigma(W_{(0)}x_t + U_{(0)}h_{t-1} + b_{(0)}) \quad (12)$$

The gate for output o_t Represents the output gates that govern the output of the memory cell. σ symbolizes the activation function of the sigmoid $W_{(0)}$ is a matrix of weights. x_t symbolizes the input at one moment. U Is The hidden layer output's weight matrixh_{t-1} reflects the short-term memory and is the concealed state. $b_{(0)}$ Does the offset vector
The concealed layer's present condition

$$h_t = o_t \odot tanh(c_t) \quad (13)$$

h_t Is the state concealed? $tanh$ is the Sigmoid activation function, c_t Is the cell state reflecting the long-term memory the output gate that regulates the output of the memory cell?

Xu [32] proposed that the Bi-L STM network acquires backwards and forward features. Therefore, this study employs the feature irregularity in the OCBs to address the issue. Bi-LSTM model to extract additional information concealed in the deep semantic relationships of the context. model to extract more information contained in the deep semantic links of the contextBi-LSTM model to extract more information contained in the deep semantic links of the context.

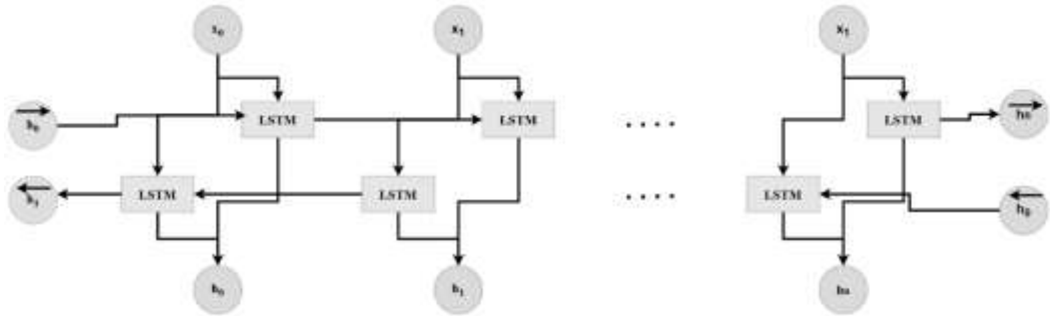

Figure 2:BILSTM network model

Equations (14) and (15) display the formulae for the state at every point in the model. of the Bi-LSTM jointly determines the final state,

$$\vec{h}_i = LSTM(x_i, \vec{h}_{i-1}) \qquad (14)$$

$$z\overleftarrow{h}_i = LSTM(x_i, \overleftarrow{h}_{i-1}) \qquad (15)$$

Temporal convolutional neural network

A novel neural network that uses convolutioncalled TCN was created specifically for sequence modeling. TCN models use Long-range patterns are captured via a hierarchy of temporal convolutional filters, and TCN improves between the receptive field and net depthby using residual block structure and dilated casual convolutions. In The receptive field of dilated casual convolutions is expanded by using dilated convolution to convolve Only items from time t and earlier in the previous layer were included in the output at time t. In contrast to ordinary convolutions, dilated convolutions introduce a predetermined pause in between neighbouring filter touches. Given a filter f:{0,….k-1}→R_ and a 1-D sequence input x∈ R^n, the convolution operation F on the sequence elements is defined as below.

$$F(s) = (x * df)(s) = \sum_{k-1}^{i=0} f(i).x_s - d_i \qquad (16)$$

Where d is the dilation factor, k is the filter size, and s-d·i quantity is the past direction, the TCN's receptive field is increased by using larger filter sizes k and increasing the dilation factor d. a dilated causal convolution structure with dilation factors d = 1, 2, 4, and k=3. TCN also uses the residual block, which has been used to build intense networks; when input and output features of a residual block are not equal, the 1 × 1 Conv layer is required because the input is resized to match the output's feature count so that they can be combined; the sum of transformation outputs and inputs is also known as skip connection. This prevents the vanishing gradient issue by carrying it throughout a deep network.

IV.METHODOLOGY

This research proposes a hybrid machine learning method combining Bidirectional Long Short-Term Memory (BiLSTM) and Temporal Convolutional Networks (TCN) to predict Indian universities based on their NIRF rankings. The method comprises several steps: data gathering, preprocessing, model creation, training, testing, and deployment.

4.1 Data collection

The "Top Engineering Colleges in India" Kaggle dataset provided by IoTTech consists of a comprehensive list of engineering colleges across India. The data would likely be replicated from reliable ranking systems such as the NIRF, or National Institutional Ranking Framework, and other evaluating metrics. It possesses essential elements such as names of institutions, rankings, geographic locations, accreditation status, teacher qualifications, students' enrollment, placement rates, research productivity, and other performance measures. The dataset can be utilized for education level analysis, institutional comparison, and student and researcher choice. It is also a vital source in identifying engineering education trends, high-performing institutions, and academic and placement opportunities.

Data Source

Source Link:

https://www.kaggle.com/datasets/iottech/top-engineering-colleges-india/data?select=update_data_of_300.csv

4.2 Data preprocessing

4.2.1 Handling Missing Values

Both numerical and categorical columns in the dataset may have missing values. To prevent skewing the data distribution, missing numerical values in rank, TLR, RPC, go, oi, and perc are filled using the median, while missing values in categorical columns such as owner_ship and grade are filled using mode imputation (Tahir et al., 2025).

4.2.2 Encoding Categorical Variables

(Benjamin, 2025b)One-hot encoding is used for owner_ship (Private/Public) and grade (AAAA, AAAAA, Other), which are categorical. This approach avoids giving categories arbitrary numerical correlations. It creates new binary columns like grade_AAAAA, grade_Other, and owner_ship_Public/Government.

4.2.3 Feature Scaling (Normalization/Standardization)

For rank, TLR, RPC, go, oi, and perc, standardization (Z-score scaling) is used to provide uniformity across numerical columns. (February et al., 2025)The dataset is appropriate for machine learning models because of this treatment, which ensures equal variance and centers the values around zero.

4.2.4 Handling Labels

To make classification easier, the label column is transformed into ordinal bins if it represents continuous ranges. There is no need for transformation if it is binary (0 or 1). This stage guarantees that the label format complies with the model specifications(Benjamin, 2025a).

4.3 Model Building

Long Short-Term Memory (BiLSTM) in both directions and Temporal Convolutional Network (TCN) are part of the proposed classification model to enhance NIRF ranking prediction accuracy and credibility. By leveraging dilated causal convolutions to handle ranking patterns over a few years, TCN is employed to extract temporal patterns and long-term interdependence between university performance indicators. This allows the model to detect subtle variations in institutional development and ranking scores. BiLSTM is employed, however, to capture accrediting information and qualitative feedback from students and instructors. BiLSTM increases the interpretability and decision-making capacity of the model by leveraging its bidirectional nature to detect influential emotions, uncover common themes, and match textual insights with ranking factors.In order to ensure confidentiality and integrity of NIRF ranking information, Blockchain Integration is embedded in the hybrid machine learning framework. It avoids data tampering and supports verifiable open authentication of institutional ranks through the decentralized and tamper-proof framework that blockchain technology provides. This renders the system of categorization robust, solid, and fraud-proof.

4.4 Performance Metrics

Accuracy: The most straightforward method of determining how often the classifier generates accurate predictions is to use accuracy. This might instead be interpreted as the proportion of all correctly predicted positive outcomes divide by the total amount of forecasts made.

$$Accuracy = \frac{TP + TN}{S} \quad (17)$$

Precision: In contrast to this ratio in addition to one minus from it, that is, (1 – precision), which displays the proportion of erroneous negatives; recall is obtained from 1/precision.

.

$$Precision = \frac{TP}{TP+FP} \quad (18)$$

Recall: However, in contrast to true negatives, there are also known as false negatives.

$$Recall = \frac{TP}{TP+FN} \quad (19)$$

F1-Score: The recall's harmonic mean and accuracy scores is used to calculate it.

$$F_1 = \frac{2*\text{Precision}*\text{Recall}}{\text{Precision}+\text{Recall}} \quad (20)$$

4.4.1 Algorithm for Model

Algorithm 1 College classification using NIRF Ranking

1: Input: Dataset from Kaggle containing engineering college rankings and attributes
2: Output: Predicted NIRF ranking class
3: Step 1: Data Preprocessing
4: Handle missing values:
5: Fill missing numerical values using median.
6: Fill missing categorical values using mode.
7: Encode categorical variables using one-hot encoding.
8: Normalize numerical features using Z-score standardization.
9: Convert label column into ordinal bins if needed.
10: Step 2: Model Building
11: Define Temporal Convolutional Network (TCN):
12: Use dilated causal convolutions to learn temporal patterns.
13: Capture long-term dependencies in ranking attributes.
14: Define Bidirectional Long Short-Term Memory (BiLSTM):
15: Process institutional accreditation and qualitative feedback.

Use bidirectional layers to capture forward and backward dependencies.
Combine TCN and BiLSTM for hybrid ranking prediction.
Integrate Blockchain to ensure ranking data integrity.
Step 3: Model Training and Evaluation
Split dataset into training and testing sets.
Train the hybrid TCN-BiLSTM model using labeled data.
Evaluate model performance using:
Accuracy:

$$Accuracy = \frac{TP + TN}{S}$$

Precision:

$$Precision = \frac{TP}{TP + FP}$$

Recall:

$$Recall = \frac{TP}{TP + FN}$$

F1 Score:

$$F_1 = \frac{2 * Precision * Recall}{Precision + Recall}$$

Step 4: Model Deployment
Deploy trained model as a web service for ranking predictions.
Ensure Blockchain integration for verifiable ranking authentication.

V. RESULTS AND DISCUSSION

Hierarchical college tier classification deep learning models are assessed here for distinguishing Tier-1 to Tier-4 colleges. Hybrid TCN+BiLSTM performs the best in terms of accuracy, particularly for Tier-4 classification. Model strengths and weaknesses are reflected by confusion matrices, ROC curves, and performance measures, whereas tier-based differences are indicated by AUC values and misclassification patterns. BiLSTM and LSTM are good, but they are not good at middle-tier differentiation, and TCN is poor in Tier-1 classification. Blockchain provides credibility and transparency to ranking, which makes this AI-based academic assessment framework strong and interpretable.

*5.1 **Confusion Matrix***

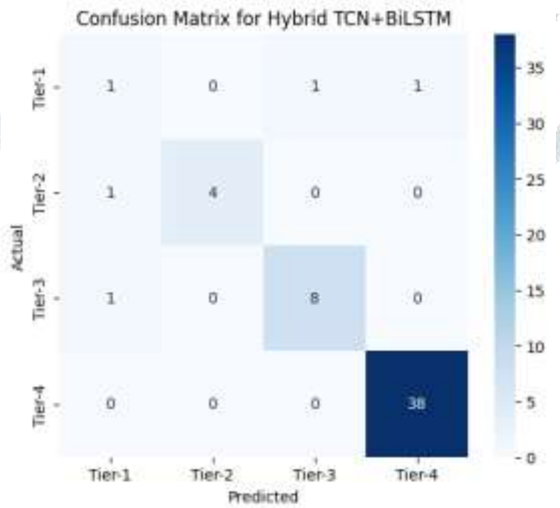

Figure 3:Confusion matrix for Hybrid TCN+BiLSTM

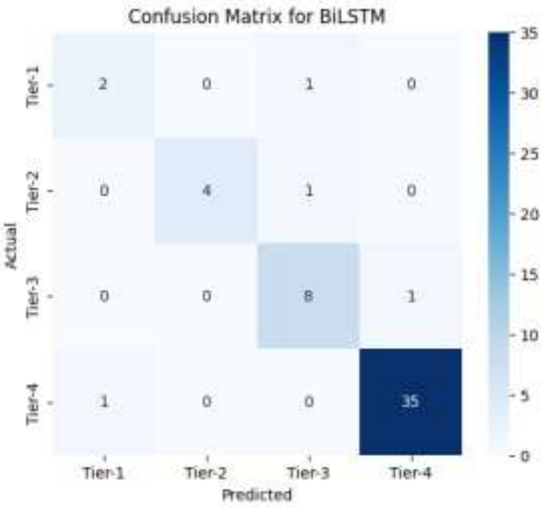

Figure 4:Confusion Matrix for BILSTM

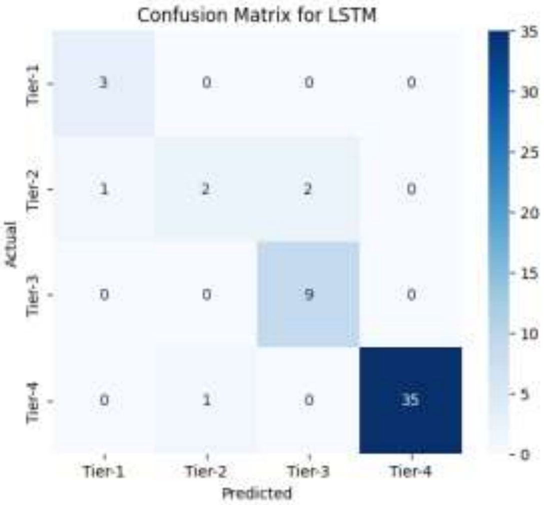

Figure 5:Confusion Matrix for LSTM

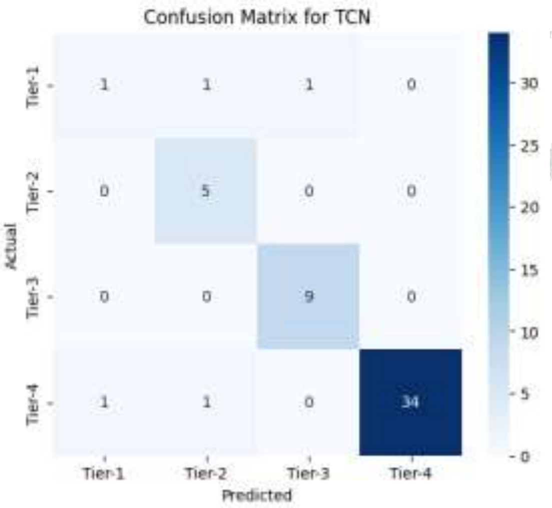

Figure 6:Confusion Matrix for TCN

The confusion matrices illustrate the efficacy of various models in categorizing college tiers (Tier-1, Tier-2, Tier-3, Tier-4) according to actual and predicted values. The Hybrid TCN+BiLSTM model, illustrated in Figure 3, exhibits robust performance, particularly in Tier-4, with 38 accurate predictions. It erroneously categorizes one Tier-3 instance as Tier-1, one Tier-1 instance as Tier-3, and one Tier-2 instance as Tier-4. The LSTM model (Figure 5) demonstrates efficacy, accurately predicting 9 instances in Tier-3 and 35 in Tier-4; however, it erroneously classifies 3 Tier-1 instances as Tier-1, 2 Tier-2 instances as Tier-2, and 1 Tier-4 instance as Tier-2. The BiLSTM model (Figure 4) exhibits comparable trends, accurately predicting 8 instances in Tier-3 and 35 in Tier-4, although it erroneously classifies 1 Tier-4 instance as Tier-1 and two instances of Tier-1 as Tier-1. TCN model (Figure 6) accurately predicts 9 Tier-3 and 34 Tier-4 instances, but erroneously classifies 1 Tier-4 instance as Tier-3 and 1 Tier-1 instance as Tier-2. The Hybrid TCN+BiLSTM model is the most effective, particularly in Tier-4 classification, rendering it an excellent option for hierarchical college tier classification. The performance in recognizing Tier-3 is promising; however, misclassifications in lower tiers indicate potential for optimization. Moreover, although all models demonstrate high accuracy in Tier-4 classification, their efficacy in differentiating between Tier-1 and Tier-2 exhibits variability, suggesting potential opportunities for enhancement in addressing nuanced distinctions between these categories.

5.2 ROC Curves:

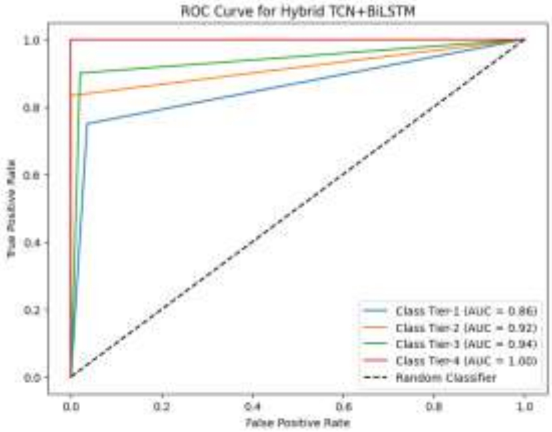

Figure 7:ROC Curve for Hybrid TCN + BiLSTM

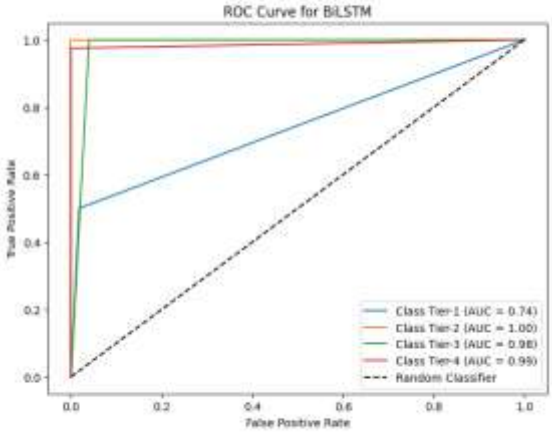

Figure 8:ROC Curve for BILSTM

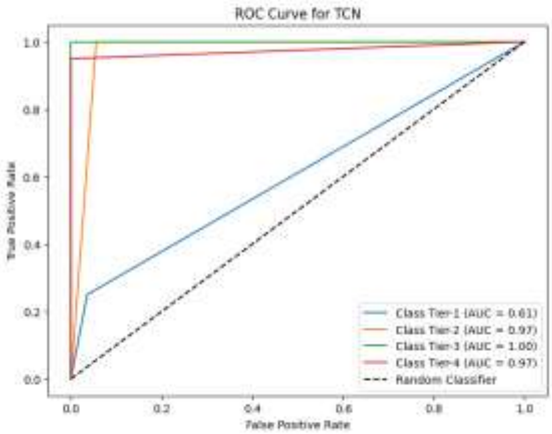

Figure 9:ROC curve for TCN

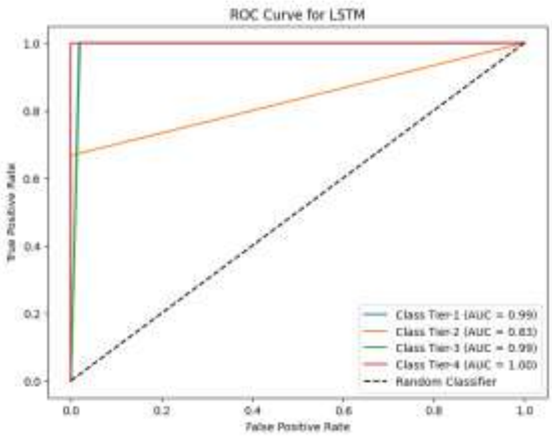

Figure 10:ROC Curve for LSTM

The ROC curves indicate the classification ability of various models in discriminating between college tiers based on their respective AUC values.

The Hybrid TCN+BiLSTM model (Figure 7) indicates outstanding performance in all tiers with an AUC of 0.86 for Tier 1: 0.92; Tier 2: 0.92; Tier 3: 0.94 and a perfect 1.00 for Tier-4, indicating its high reliability in discriminating between college tiers, and more specifically indicating outstanding performance in Tier-4 classification.

The TCN model (Figure 9) indicates poor performance for Tier-1 with an AUC of 0.61, but indicates good effectiveness for Tier-2 (0.97), Tier-3 (1.00), and Tier-4 (0.97), indicating its vulnerability in Tier-1 classification but high effectiveness in higher tiers.

The BiLSTM model (Figure 8) indicates good performance with an AUC of 0.74 for 0.92 for Tier 1, 0.92 for Tier 2, and 0.94 for Tier 3. , and 0.99 for Tier-4, indicating its high capability in higher-tier classifications but areas of improvement in Tier-1 accuracy.

The LSTM model (Figure 10) indicates an AUC of 0.99 for Tier 1: 0.83; Tier 2: 0.83; Tier 3: 0.99, and 1.00 for Tier-4, indicating high capability in most classifications but a bit weakness in Tier-2.

The Hybrid TCN+BiLSTM model is exceptional with its consistent and balanced capability to classify all levels, and thus is the best option, especially in discriminating between lower-tier colleges while indicating excellent performance for higher tiers.

5.3 Performance metrics

Table 1:Performance of all models

Model	Accuracy	Precision	Recall	F1 Score
Hybrid TCN + BiLSTM	0.9273	0.9008	0.8933	0.9004
BILSTM	0.9074	0.8597	0.8393	0.8459
LSTM	0.8941	0.8087	0.8431	0.8108
TCN	0.8874	0.77866	0.8194	0.7881

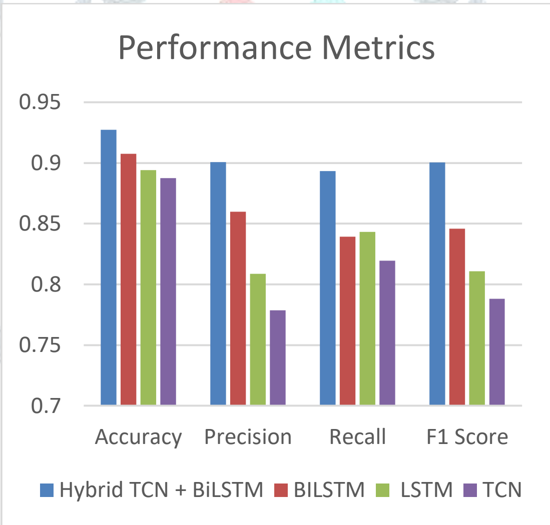

Figure 11:Bar Chart for models' performance

The bar graph displays each individual's relative performance. models as compared to each other in terms of F1-score, recall, accuracy, and precision. By recording an accuracy of 0.9273, precision of 0.9008, recall of 0.8933, and F1-score of 0.9004, the Hybrid TCN + BiLSTM model performs better than the others. thus, making it the most effective architecture amongst those tested. The BiLSTM model achieves an F1-score of 0.9074, recall of 0.8393, precision of 0.8597, and accuracy of 0.8459, reflecting strong classification performance. The LSTM model obtains an F1-score of 0.8941, recall of 0.8431, accuracy of 0.8941, and precision of 0.8087. 0.8108, reflecting competitive performance, although slightly weaker than BiLSTM. The model with the least performance is the TCN model, with performance metrics of F1-score = 0.8874, recall = 0.8194, precision = 0.77866, and accuracy = 0.7881.

The bar chart clearly represents the outstanding performance of the Hybrid TCN + BiLSTM model, setting it as the most reliable method for the task at hand to be classified.

5.4 Discussion

The findings highlight the efficiency of the Hybrid TCN + BiLSTM model for correctly using data to determine college levels security and integrity ensured through blockchain incorporation. The confusion matrices reveal that the model achieves maximum accuracy in Tier-4 classification, making it the most reliable to distinguish top-tiered institutions. However, Tier-1 and Tier-2 misclassifications indicate room for improvement, particularly in the discrimination of subtle differences between these tiers. Cross-validation with other models shows that while BiLSTM and LSTM are impressive performers, they have relatively lower accuracy in discriminating between the middle tiers. The

TCN model, while very good in higher-tier categorization, struggles with significant impairment in Tier-1 classification, as seen through its lower AUC for the class. The ROC curve analysis also confirms the dominance of the Hybrid TCN + BiLSTM model, which consistently has high AUC values across all levels, confirming its performance in discriminating institutions according to their ranks. The even performance of this model across all levels makes it a best choice for hierarchical classification, while other models have limitations in specific categories. The findings show that while conventional models like LSTM and BiLSTM do improve performance, their performance is further increased when combined with Temporal Convolutional Networks to enable better feature extraction as well as the learning of long-range dependencies. The integration of blockchain technology not only assures verifiability but also reinforces the credibility of institutional rankings, making it a necessary part of the framework. This research highlights the importance of explainability in AI ranking systems, given that understanding model flaws and limitations is crucial to improving methodologies and ensuring fair and transparent assessments.

VI. CONCLUSION

The significance of applying deep models of learning for university ranking reviews and academic feedback systems. The study highlights that the integration of Temporal Convolutional Networks with BiLSTM gives rise to an improved classification framework, enabling productive tier-based grouping of colleges. The outcome shows that decision-making in the academic sector could be enhanced with the use of sophisticated neural architecture, offering data-driven means to evaluate institutional performance. While the findings are promising, follow-up studies might explore additional improvement areas, such as incorporating outside academic ranking variables, the addition of transformer models, and improving feature extraction strategies. The methodology of this study provides an extensible and adaptable solution deployable in most educational environments and thus improves the rankings of universities using advanced business analytics. In addition, the ability to automate and improve classification of institutions can aid policymakers, researchers, and administrators in devising focused policies for institutional development. Deep learning methods are used in this study to obtain meaningful results from educational information in line with the broader aim of enhancing efficiency and transparency of academic assessment mechanisms critical to nurturing continued progress in higher education.

VII. REFERENCES

Amato, F., Galli, A., Gravina, M., Marassi, L., Marrone, S., & Sansone, C. (2023). AI-Powered Learning: Personalizing Education for each Student. *CEUR Workshop Proceedings*, *3486*, 478–483.

Balaji, N. G. (2024). *HOW TO INCREASE UNIVERSITY WORLD RANKING : A CASE STUDY*. *13*(3), 1–12.

Benjamin, M. (2025a). *Handling Categorical Variables in Ensemble Algorithms Author : Matthew Benjamin Date : 5 th Feb 2025 Abstract : February*.

Benjamin, M. (2025b). *Hybrid Feature Encoding Techniques for Ensemble Learning Author : Matthew Benjamin Date : 5 th Feb 2025 Abstract*. *February*.

Cardoso, E., & Su, X. (2022). Designing a Business Intelligence and Analytics Maturity Model for Higher Education: A Design Science Approach. In *Applied Sciences* (Vol. 12, Issue 9). https://doi.org/10.3390/app12094625

Chen, Z. (2024). *A Study on Employment Problems and Sentiment Analysis of College Students Based on Bert-BiLSTM* (Issue Iciaai). Atlantis Press International BV. https://doi.org/10.2991/978-94-6463-540-9

Dabhade, P., Agarwal, R., Alameen, K. P., Fathima, A. T., Sridharan, R., & Gopakumar, G. (2021). Educational data mining for predicting students' academic performance using machine learning algorithms. *Materials Today: Proceedings*, *47*, 5260–5267. https://doi.org/https://doi.org/10.1016/j.matpr.2021.05.646

February, V. N., Palaniappan, S., Logeswaran, R., Khanam, S., & Yujiao, Z. (2025). *Machine Learning Model for Predicting Net Environmental Effects*. *4*(1).

Feng, Y., Zhu, J., Qiu, P., Zhang, X., & Shuai, C. (2024). Short-term Power Load Forecasting Based on TCN-BiLSTM-Attention and Multi-feature Fusion. *Arabian Journal for Science and Engineering*. https://doi.org/10.1007/s13369-024-09351-5

Gopali, S., Abri, F., Siami-Namini, S., & Namin, A. S. (2021). A Comparison of TCN and LSTM Models in Detecting Anomalies in Time Series Data. *2021 IEEE International Conference on Big Data (Big Data)*, 2415–2420. https://doi.org/10.1109/BigData52589.2021.9671488

Gupta, S., Sushil, S., & Gulati, K. (2025). Transformation of national ranking score for positioning higher education institutions in international ranking–a case on India. *International Journal of Productivity and Performance Management*.

Henderson, M., Ryan, T., & Phillips, M. (2019). The challenges of feedback in higher education. *Assessment & Evaluation in Higher Education*.

Hmoud, H., Al-Adwan, A. S., Horani, O., Yaseen, H., & Zoubi, J. Z. Al. (2023). Factors influencing business intelligence adoption by higher education institutions. *Journal of Open Innovation: Technology, Market, and Complexity*, *9*(3), 100111. https://doi.org/https://doi.org/10.1016/j.joitmc.2023.100111

Hu, Y. (2024). Application of Blockchain Technology and TCN-IS Model on Financial Risk in Universities. *2024 2nd International Conference on Mechatronics, IoT and Industrial Informatics (ICMIII)*, 522–526. https://doi.org/10.1109/ICMIII62623.2024.00103

Kastrati, Z., Dalipi, F., Imran, A. S., Nuci, K. P., & Wani, M. A. (2021). Sentiment analysis of students' feedback with nlp and deep learning: A systematic mapping study. *Applied Sciences (Switzerland)*, *11*(9). https://doi.org/10.3390/app11093986

Khan, A. A., Laghari, A. A., Shaikh, A. A., Bourouis, S., Mamlouk, A. M., & Alshazly, H. (2021). Educational blockchain: A secure degree attestation and verification traceability architecture for higher education commission. *Applied Sciences (Switzerland)*, *11*(22), 1–22. https://doi.org/10.3390/app112210917

Kumar, A., Singh, K., & Siwach, A. (2021). NIRF India Rankings 2020 Analyzing the Ranking Parameters and Score of Top 100 Universities. *DESIDOC Journal of Library & Information Technology*, *41*, 385–390. https://doi.org/10.14429/djlit.41.5.16452

Pallathadka, H., Wenda, A., Ramirez-Asís, E., Asís-López, M., Flores-Albornoz, J., & Phasinam, K. (2023). Classification and prediction of student performance data using various machine learning algorithms. *Materials Today: Proceedings*, *80*(July), 3782–3785. https://doi.org/10.1016/j.matpr.2021.07.382

Shaik, T., Tao, X., Dann, C., Xie, H., Li, Y., & Galligan, L. (2023). Sentiment analysis and opinion mining on educational data: A survey. *Natural Language Processing Journal*, *2*, 100003. https://doi.org/https://doi.org/10.1016/j.nlp.2022.100003

Shaik, T., Tao, X., Li, Y., Dann, C., McDonald, J., Redmond, P., & Galligan, L. (2022). A Review of the Trends and Challenges in Adopting Natural Language Processing Methods for Education Feedback Analysis. *IEEE Access*, *10*, 56720–56739. https://doi.org/10.1109/ACCESS.2022.3177752

Singla, P., Duhan, M., & Saroha, S. (2022). An ensemble method to forecast 24-h ahead solar irradiance using wavelet decomposition and BiLSTM deep learning network. *Earth Science Informatics*, *15*(1), 291–306. https://doi.org/10.1007/s12145-021-00723-1

Tahir, M., Abdullah, A., Udzir, N. I., & Kasmiran, K. A. (2025). A novel approach for handling missing data to enhance network intrusion detection system. *Cyber Security and Applications*, *3*, 100063. https://doi.org/https://doi.org/10.1016/j.csa.2024.100063

Wang, S. (2023). A Stock Price Prediction Method Based on BiLSTM and Improved Transformer. *IEEE Access*, *11*, 104211–104223. https://doi.org/10.1109/ACCESS.2023.3296308

Zhang, H., & Chu, P. (2024). *Prediction Study Based on TCN-BiLSTM-SA Time Series Model* (Issue Icidit 2023). Atlantis Press International BV. https://doi.org/10.2991/978-94-6463-266-8_21