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VOCATIONAL EDUCATION SKILL ASSESSMENT AND INTELLIGENT ASSISTANCE: A STUDY ON THE APPLICATION OF MACHINE LEARNING ALGORITHMS IN THE ASSESSMENT OF VOCATIONAL INFORMATION LITERACY TEACHING ABILITY

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ABSTRACT

Vocational education skill assessment and intelligent assistance involve evaluating people' talent in precise vocational abilities and conveying personalized assist to enhance studying results. The need for such assessment and assistance arises from the significance of appropriately evaluating learners' readiness and proficiency in vocational abilities, identifying areas for improvement in teaching practices, and presenting timely feedback and guidance to learners. However, present strategies often depend on conventional assessment techniques which can lack granularity and fail to provide personalised assistance. To address those demanding situations, this study introduces a novel method that integrates SMOTE data processing, Federated LSTM (Fed-LSTM) for skill word extraction and classification, and fuzzy rule-based vocational education talent evaluation. This approach targets to overcome class imbalances in datasets through SMOTE, permit collaborative learning across distributed data sources, and improve the accuracy and robustness of talent assessment models. The proposed study improves data representation, facilitating collaborative learning, enhancing skill extraction accuracy, and presenting robust skill assessment. The results of study are applied in a Python software, offering educators and stakeholders a realistic approach to enhance vocational education skill assessment and intelligent assistance. The proposed Fed-LSTM technique demonstrates a substantial growth in accuracy compared to the LSTM approach. With an accuracy of 99.4%, the proposed technique considerably outperforms the LSTM method, which achieved an accuracy of 76. 98%. This represents a substantial improvement of 22.42% in accuracy.

Keywords—*Vocational Education, Skill Assessment, Intelligent Assistance, Teaching Practices, Synthetic Minority Oversampling Technique*

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1. INTRODUCTION

Vocational education is a formal educational program focused on the growth of practical abilities. The vocational emphasis of vocational education is its primary distinguishing trait, either for a specific reason of acquiring job-related abilities, supplementing general understanding with direct or practical lessons, or cultivating values such as participation and morality [1] [2] [3]. Although any educational topic could potentially connect to and improve production beyond educational institutions, researchers want to define technical training's binary data job-focused characteristic to distinguish it from broad education. As an initial starting point, consider three key models and consider educational institutions as developing understanding and skills that are certain to specific enterprises or vocations as opposed to being broadly transferable among enterprises [4] [5]. The result for training and instruction is that corporations had a vested interest in delivering specific to the company, instead of general, learning, requiring individuals to develop broad abilities independently. In Lazear's instance, an application firm that provides tax reduction solutions requires employees who are knowledgeable in a unique combination of economics, accounting, and computing. The skill-weighting notion goes beyond the corporation to the profession. A skilled communication expert relies on training, education, or professional expertise in the fields of graphic design, text, advertising, and their company's business [6]. Nevertheless, not every one of the higher education disciplines are given significant value by an average organization. Some issues are simply smaller as other. In view of that, researchers suggest an additional characteristic of occupational learning: a general, ongoing indicator of broader specific application between occupations.

Vocational training varies greatly over this range, with a tendency to be shorter. merely mapped vocational courses to jobs, the relationship might be individually or one-to-few rather than multifaceted or one-to-all [7] [8]. An occupations-focused education, often applicable to a small number of occupations, is an encompassing theoretical structure for vocational training, but it additionally includes many areas that cannot be considered occupations, such as religion, musical performances, the field of engineering, or regulations, to name some of them. To compress this frame even more and make it nearer to vocational training as it occurs in both study and practice, researchers introduce an additional component depending on socioeconomic standing or aptitude. Vocational education programmes usually build information for middle-skilled or lower-income employment. Building, producing goods, management of offices, and fields of agriculture are some of the more prominent and common applications [9] [10] [11]. The determined by class classification of occupational and general education courses is most visible in countries where learners enter secondary education choosing between a university in preparation or occupational course, with the occupational track culminating in an advanced graduation that is unable to be used as a basis for admission to top colleges and universities. Within improved educational systems, teachers, administrations, and residents promote vocational training as an alternative to financial stability or job advancement that does not necessitate undergraduate or graduate attendance. And certainly, vocational training isn't only available in secondary school students. Most of the educational process that occurs in higher education institutions is occupational in the environment, both in regards to skill applicability and the socioeconomic level of positions in which these skills are required. In simple terms, the scope and complexity of vocational training differ amongst nations [12] [13].

As a result of the usage of Industry 4.0-based technology in facilities and a broader connectivity of employment and company procedures within enterprises, job requirements for qualified employees shift. Components of connecting and reasoning inside connected systems become more vital for highly trained employees on the manufacturing floor. As manufacturing becomes more automated, skilled employees' occupational tasks are changing: they must finish their tasks with computerized devices, work manufacturing facilities using interfaces between humans and machines, and enhance their competence with the assist of computerized media outlets, support infrastructure, and collaborative effort frameworks. The growing convergence of information technology and conventional methods of production is becoming more visible [14]. There are several challenges in vocational educational, such as evolving educators' behaviours to use scientific techniques, student-focused and passive educational habits, restricted communication and cooperation over studying, inadequate utilization of role technological advances, and difficulty in educating teachers [15]. A few of the challenges learners face are related to their abilities. Individuals have poor analytical and innovative problem-solving ability. In today's world, teachers' contribution to learning requires enhanced abilities to learn. Quick response is needed to address the challenges of modernizing vocational and technical education and training programs [16] [17]. Student-centred education focuses on solving problems, analytical thinking, creativity, collaboration, interpersonal relationships, and proficiency with technology, replacing traditional instructional methods. In-depth analysis is needed to assess the challenges learners and educators face when integrating twenty-first-century learning based on competencies[18]. This study will assess educators and students' challenges in integrating problem-oriented education, analytical thinking, creativity, collaboration, communication, and technological literacy. The aim of this research will compare the challenge in controlling and adhering to twenty-first-century competency-based instruction among teachers and students. The paper discusses the use of machine learning algorithms, specifically SMOTE data processing and Fed-LSTM, in assessing vocational information literacy teaching ability. It uses the O*NET dataset to address class imbalance and skill extraction challenges in vocational education. The research aims to improve the accuracy and robustness of talent assessment models by balancing class distributions and using Fed-LSTM for skill word extraction and classification. The study contributes to the field of vocational education by introducing novel techniques and improving the effectiveness of skill assessment models while maintaining data privacy and security. The findings have significant implications for educators, policymakers, and employers, as they enhance the ability to identify learners' readiness and proficiency in vocational abilities, inform targeted interventions, and enhance learning outcomes. The study's key contributions are as follows:

- The SMOTE data processing approach addresses class imbalances in vocational education datasets, ensuring a more consultant and balanced distribution of information. This leads to advanced model training by presenting the Fed-LSTM version with an extra various and comprehensive dataset for talent word extraction and classification.
- Employing the Federated LSTM (Fed-LSTM) model helps collaborative learning across distributed information resources, preserving data privateness while allowing for collective model training. This collaborative framework allows the combination of data from multiple vocational institutions, enhancing the version's generalization and robustness.
- The integration of a fuzzy rule-based approach for vocational education talent evaluation enhances the model's capacity to interpret and examine complicated skill profiles. By incorporating fuzzy logic principles, the assessment procedure becomes more adaptable and resilient to uncertainties and variations in student skill profiles, resulting in more accurate and reliable assessments.

This study's rest of the structure is organized as follows. Section 2 includes the previous research on the vocational education skill assessment. Problematic statement discussed in section 3. Section 4 discussed the proposed SMOTE with Fed-LSTM method. The outcomes, and discussion of findings is discussed in section 5. Section 6 provides the conclusion of the paper.

2. RELATED WORKS

Peng, Wang, and Yan [19] analyse the difficulties that vocational institutions possess while training for new abilities events and provide appropriate solutions. It highlights uncertainties among restrained budget, new arrival and capability for educators' inadequate recompense mechanisms, and curricular incompatibility. This study addresses the difficulties based on complete research and evaluation. Recommendations encompass measures to boost scholar engagement, enlarge financial assistance, supply continuing training chances to educators, remodel the machine for worthwhile fulfilment, and connect the instructional application with competitions standards. By employing those strategies, vocational institutions can encourage scholar involvement, improve the first-class of training, close the education-enterprise discrepancy, and put together graduates for accomplishments in new skill contests. The study's focus on a specific context may moreover restriction its applicability to vocational institutions in distinct regions with unique socioeconomic or cultural backgrounds. The feasibility and effectiveness of the suggested solutions may range relying at the resources and assist available to exclusive establishments. It may not address all potential demanding situations faced with the aid of vocational establishments, and there may be additional factors influencing student engagement and educator ability that had been no longer completely explored. The implementation of the suggestions may also come across obstacles or unintended results.

Ilic et al. [20] conduct an evaluation of performance of predicted obligatory adjustments, addressing the study's issue presented in this work. Panel study is currently in progress, including an analysis of the conceptual additives of reachable understanding and expertise. Publications and studies from numerous shops, which include research courses and establishments, served as materials. Also, educational research papers, and experiments on the fields of synthetic intelligence,

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artificial intelligence, machine learning, and broader truth had been reviewed. The researchers trust that such tools might be extraordinarily useful in building a modern educational method. The information accumulated from one hundred Serbian students across chosen institutions of higher getting to know has been applied to assess whether those advances in generation are embraced by way of students. The observer's assessment demonstrated that AI and ML constitute suitable strategies to be utilized by colleges and universities to improve learner's abilities, create an environment for cooperative getting to know, and make study quite simply available. Extended fact encourages more idea, engagement, and look at-by using-doing behaviours amongst novices, providing a proper learning environment. The ability for sampling bias, because the study focused exclusively on a hundred Serbian students from selected establishments. This restricted pattern length and geographic scope might not appropriately constitute the diversity of views and studies among college students international. It's reliance on self-pronounced facts and subjective exams of the usefulness of AI, ML, and extended truth equipment can also introduce reaction bias and limit the reliability of the findings. It may also restriction the intensity of analysis and prevent definitive conclusions about the effectiveness of those technologies in improving learning outcomes. The attention on technology adoption may overlook other factors influencing student engagement and learning, inclusive of educational methods and institutional assist systems. The study's reliance on contemporary developments in technology may not interpretation for future trends or adjustments in educational practices.

Shi, Peng, and Sun [21] suggested an approach for improving data literacy among students in college based on an innovative environment for learning. Based on past studies and academic analysis, researchers propose the components of an effective educational setting for developing students' higher education information literacy. All of them, together known as CIAP, are divided into four categories: conceptual in nature, intellectual, behaviour, and procedure levels. Based on CIAP, researchers suggest a novel blended educational paradigm for improving students' college-level literacy in information technology in a sustainable manner. The findings show that a blended learning approach based on the smart environment for learning suggested in this research has a substantial impact on the development of literacy in information among students in college. This study explores the continuous growth in literacy in information made possible by the intelligent educational atmosphere. The results of our study on the mindset and strategy of the long-term growth of digital literacy education was optimistic. Enhancing data literacy amongst college students won't capture the entire variety of strategies and interventions that could be effective in educational setting or with different scholar populations. The reliance on self-reported records or subjective tests of the effect of the mixed learning technique may introduce response bias and limit the validity of the outcomes. The study's emphasis on lengthy-time period boom in virtual literacy education may additionally forget about brief-time period challenges to implementation that might have an effect on the sustainability of the proposed method. Finally, the examine might not completely consider potential ethical or privacy concerns related to the usage of clever environments for gaining knowledge of in academic settings.

Zhang et al. [22] suggest that learners need to understand the three fundamental areas of AI: technological principles and methods, moral and social ramifications, and professional opportunities in the artificial intelligence era. This study details the development and execution of the Developing AI Literacy (DAILy) class, which focused on integrating elementary school students' education across three different areas. Following the development of the program, researchers discovered that the majority of learners had a general comprehension of AI fundamentals and processes. More crucially, they had been able to detect bias, outline methods for mitigating bias in algorithmic learning, and begin to evaluate how AI would affect their lives afterwards and jobs. At the end, more than fifty percent of the learners indicated that AI is more than just a technological study; it has intimate, occupation, and social ramifications. Overall, our finding implies that adding ethics and professional prospects into AI instruction is both age suitable and beneficial in increasing AI literacy amongst elementary school children. This study advances the discipline of AI Learning by offering a strategy for incorporating ethics into AI instruction that is suited for middle-school students.

Chen, Sakyi, and Cui [23] want to determine which components from the learner's home, and educational environments are especially essential in distinguishing excellent technological devices from low-performing digital users. Except for traditional literacy stages, among the most significant contextual elements leading to digital users' excellent performance were students' reading confidence in oneself, using at home materials, discussing what they had read in class, and the number of publications in their homes. The identified 20 essential contextual features have a significant predictive value for differentiating digital users. The results of our research reveal that, when it comes to general, such as home-related elements have a larger impact on children's digital literacy progress; at the educational level, instruction-related aspects become more important than characteristics of the school. The study's focus on unique contextual functions may additionally disregard the complex interaction of different factors that influence digital literacy effects, consisting of socioeconomic character, parental training stage. The reliance on self-reported statistics or subjective exams of reading self-assurance and home substances may also introduce response bias and restriction the reliability of the findings. The sample size may not be representative of the wider populace, excluding the generalizability of the outcomes. The study's move-sectional design won't capture longitudinal modifications in virtual literacy performance or account for potential confounding variables.

Hidalgo et al. [24] examined how the growing popularity of ICT in work environments has resulted in an increasing needs for novel abilities and digital skills, whether in the development of goods and solutions or in the search for individuals with complementing talents. Problems regarding disparity in access to new methods, which are incorporated into the idea of the technological divide, have been the subject of research since the widespread usage of the Internet. In the past, study about the inequities caused by the rise of technological advancements has included socioeconomic factors such as age and gender, level of education, earnings, and environment. This study uses extensive methods for data analysis to examine the primary socioeconomic digital abilities determinants in the Spanish population. This data makes it possible to determine whether individuals require education in digital competencies, which can have a good impact on the nation's overall degree of sustainable growth. The reliance on self-reported information for socioeconomic factors and digital abilities may also introduce feedback bias and have an effect on the accuracy of the consequences. The study's cross-sectional design may not capture longitudinal adjustments in virtual competencies or account for capability confounding variables. The study examines socioeconomic determinants of virtual competencies, it cannot absolutely discover other elements inclusive of cultural impacts or access to educational sources that could additionally impact virtual abilities development. The findings may be stimulated by the particular methods selected for data evaluation, which can have an effect on the robustness of the conclusions strained.

The discussed studies explore numerous facets of education, supplying insights into enhancing learning outcomes and virtual literacy amongst students. One study identifies demanding situations faced by vocational establishments and proposes answers to improve student engagement and academic quality. Another examines the capacity of AI and ML in education, noting advantages in enhancing learning experience though cautioning in opposition to overlooking other influential factors. A blended learning method to improve statistics literacy, emphasizing the combination of era into training. Teaching AI ethics to essential school students, showcasing effective educational strategies. Another study investigates contextual elements affecting virtual literacy, underscoring need for personalized educational interventions. Socioeconomic determinants of virtual capabilities, emphasizing the significance of addressing differences in skill access for sustainable growth.

3. PROBLEM STATEMENT

The literature studies highlight various challenges and opportunities in education, mainly inside the domains of vocational education, generation integration, and digital literacy. One problem identified is the disparity in access to the high-quality education and sources, that may delay college students' learning outcomes and ordinary skill improvement. There are challenges related to addressing class imbalances and enhancing the accuracy and effectiveness of vocational education ability evaluation procedures. Traditional strategies might also conflict to competently cope with those problems, leading to suboptimal learning experiences and consequences for college students [21] [22]. To overcome those challenging situations, this study proposes a novel technique that integrates SMOTE data processing with a Federated LSTM (Fed-LSTM) model for the evaluation of vocational data literacy training ability. SMOTE data processing can effectively address class imbalances in vocational training datasets, making sure that the model is educated on a more representative and balanced dataset. The Fed-LSTM model, utilising federated learning strategies, permits collective training throughout disbursed data while preserving information privacy. This method allows for correct ability word extraction and classification, leading to more effective vocational training skill assessment. Employing a fuzzy rule-based technique for vocational education ability assessment further enhances the model's accuracy and robustness.

Fed-LSTM is a machine learning technique that can improve the accuracy of vocational information literacy teaching ability assessment. It uses temporal dependencies in textual data to extract and classify skill-related words, providing a more nuanced understanding of learners' non-technical skills proficiency. Fed-LSTM also allows collaborative model training across distributed data sources,

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preserving data privacy and ensuring scalability across diverse vocational contexts. This approach addresses the limitations of conventional assessment methods.

4. PROPOSED SMOTE WITH FEDERATED LSTM MODEL FOR THE ASSESSMENT OF VOCATIONAL INFORMATION LITERACY TEACHING ABILITY

The proposed study utilizes the O*NET dataset, which offers comprehensive data on vocational education features and requirements. Following this, SMOTE data processing approaches are carried out to address class imbalance problems and improve the representativeness of the dataset. Next, Fed-LSTM is employed for skill word extraction and classification, making use of federated learning strategies to collaboratively educate a recurrent neural network model across allotted data sources at the same time as maintaining data privateness. Subsequently, a fuzzy rule-based approach is utilized for vocational education talent evaluation, leveraging predefined rules and criteria to assess the proficiency and relevance of extracted competencies within the vocational education context. These steps together allow the extraction, classification, and assessment of vocational capabilities, contributing to a complete understanding of talent necessities and informing educational practices. Fig.1 shows the methodology process of the proposed SMOTE with Federated LSTM Model in the Assessment of Vocational Information Literacy Teaching Ability.

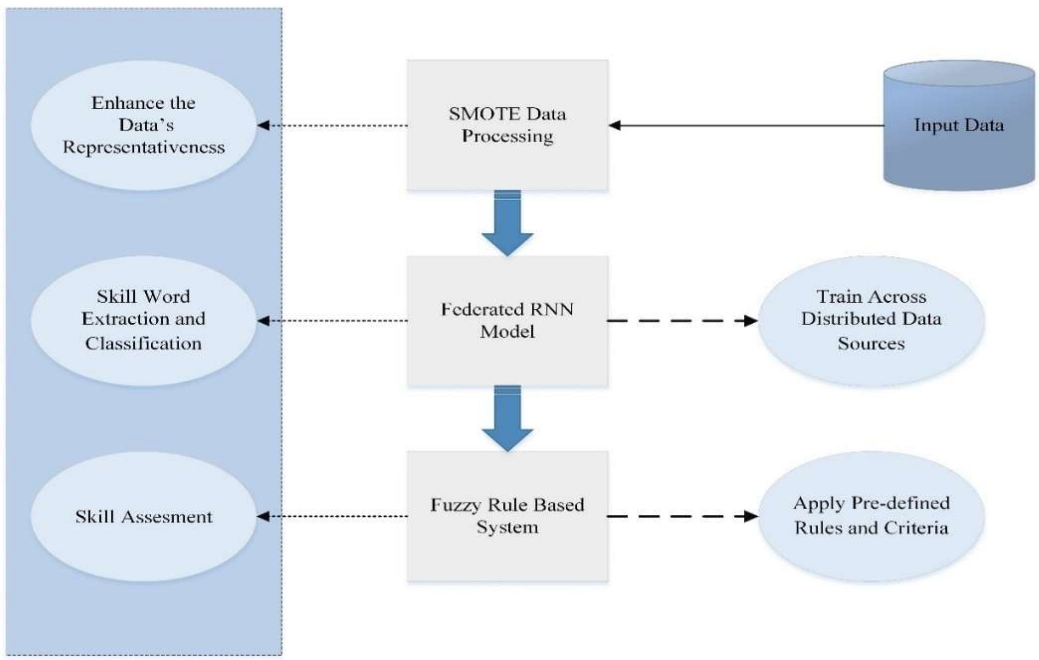

Fig. 1. Block Illustration For The Proposed SMOTE With Fed-LSTM Model

A. Data Collection

The O*NET dataset includes hundreds of standardized occupation-specific descriptions that are frequently updated through surveys of a diverse workforce. O*NET collects data on 969 jobs from the Standardized Occupation Classification (SOC) framework using 277 characteristics. The O*NET dataset is revised every year, providing images of employment functions and abilities via a continuous poll of employees from every job. This study utilized the 2019 yearly O*NET database. It provides an extensive summary of non-technical abilities needed for various occupational roles. Identifying the importance of these abilities across various positions can be tricky due to their cross-functional nature. O*NET's extensive study on combining ability levels and work responsibilities through employee surveys and interviews provides valuable insights into the importance of skills that are not technical such as 'attention to detail' for various job kinds. It provides a complete set of questionnaires for individuals to self-evaluate their abilities. Evaluating skills that are not technical with questionnaires has limits. Effective communication in numerous formats is an intricate problem that cannot be answered with a simple question. Self-evaluation, on the opposite hand, is very biased. To ensure reliability, a verified questionnaire was crucial [25].

B. SMOTE Data Processing

SMOTE is useful for addressing class imbalance problems within the dataset, especially if positive

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skills or competencies are diminished. However, it is critical to validate the effectiveness of SMOTE-generated samples and ensure they appropriately constitute the target skill distribution in vocational education. The Synthetic Minority Oversampling Technique is a preparation of information technique designed to handle uneven data. Unbalanced data impairs machine learning efficiency. The unbalanced data happens as a result of unbalanced distributions of classes in a dataset, which causes the wrong distributions to be chosen when developing a model because the dominant class is much larger than the minority. The uneven data can be dealt in two ways. To begin, it can be handled by allocating unique prices to training instances. Secondly, it can be solved by re-sampling the initial collection of data. SMOTE operates by generating fake items from a minority group. Oversampling is of the minority class necessitates the selection of k nearest neighbours at randomness [26]. Eqn. (1) shows how to find a sample from the minority class's nearest neighbour based on Euclidean distance. y *and* z indicates minority statistics. D (y, z) indicates the Euclidean distance between minority data points, while n denotes the smallest number of characteristics.

$$D(y,z) = \sqrt{(y_1 - z_1)^2 + \cdots + (y_n - z_n)^2} \tag{1}$$

The linear interpolation algorithm is then used to produce sample information from two minority data sets. From Eqn. (2), x provides synthetic data, while x reflects minority data. n is the greatest number of characteristics, and random (0,1) indicates a random number from 0 to 1.

$$x = y_n + random\ (0,1) \times (y_n - z_n) \tag{2}$$

In this study, SMOTE is used to improve the quality of the LSTM for classify literacy teaching skills and improving the accuracy of classifiers for a minority class.

C. Employing Fed-LSTM for Skill Word Extraction and Classification

Due to the capacity to simulate temporal dependencies found in a variety of applications, such as natural language processing, LSTMs, are currently gaining enormous popularity in relevant information. However, training with lengthy sequences of data is hindered by ordinary LSTMs' issues with gradients disappearing and expanding. In order to improve management of the way gradient flows within the cell, LSTM systems introduce more gates. The LSTM unit is seen in Fig.2, and the mathematical calculation of it at time t is provided in Eqn. (3) to (7).

$$I_t = \sigma(X_{yi}y_t + b_{yi} + X_{hi}h_{t-1} + b_{hi}) \tag{3}$$

$$f_t = \sigma(X_{yf}y_t + b_{yf} + X_{hf}h_{t-1} + b_{hf}) \tag{4}$$

$$O_t = (X_{yO}y_t + b_{yO} + X_{hO}h_{t-1} + b_{hO}) \tag{5}$$

$$C_t = f_t \cdot C_{t-1} + I_t \cdot \tanh\,(X_{yg}y_t + b_{yg} + X_{hg}h_{t-1} + b_{hg}) \tag{6}$$

$$h_t = O_t \cdot \tanh\,(C_t) \tag{7}$$

Here, the cell state is represented by C, its hidden state by h, and the input, forget, and output gates are represented by I, f, and O. The function that activates the sigmoid is denoted by σ, and the elementwise multiplying is represented by the representation of (·). The weights that are input-hidden and hidden-hidden are X_y and X_h , while the associated bias is b_y and b_h. The federated learning strategy uses LSTM structure to gain knowledge from sequential students' performance data because of this storage system, which enables LSTMs to succeed in vocational education skill assessment.

In federated learning, neural networks with deep layers are chosen because neural networks use the technique of gradient descent for updating the models they learn. The last type of user adaption can benefit from an already trained model obtained by the federated learning approach. Initially, datasets are used to setup the framework on the central server during the training phase. The process of learning function's objectives as stated by Eqn. (8), where f_g stands for the original global model.

$$Arg \min_g \ell = \textstyle\sum_{i=1}^{N} \ell(z_i, f_g(y_i)) \tag{8}$$

While forecasting load is an issue of regression, the loss employed in this study is mean squared error (MSE) loss, where $\ell(.)$ represents the loss for the neural network. The samples taken from databases are represented by $(y_i, z_i)_{i=1}^{N}$. All other devices will receive the model from the central server once the original global model has been developed. Next, a portion of the distant devices are selected so that local information may be used to train the user's models f_v. In the context of technology, every student's goal for learning functions is represented by Eqn. (9).

$$Arg \min_V \ell = \textstyle\sum_{i=1}^{N^v} \ell(z_i^v, f_v(y_i^v)) \tag{9}$$

After that, every user model is sent to the central server in order to average them using the Federated

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Average algorithm. Eqn. (10) for averaging is as follows:

$$f_{g'}(w) = \frac{1}{k}\sum_{k=1}^{N} f_{v_k}(w) \quad (10)$$

The total number of devices in the selected subgroup is denoted by k, and w represents the network's operational variables. The modified server's approach, $f_{g'}$, performs better in terms of ability to generalize after a sufficient number of variations, let $f_g = f_{g'}$ on the central server. Federated learning may address initial setup issues and is expandable with literacy teaching skills that are linked to the federated network. This allows the central server to share the global model to assist fresh devices in participating in the subsequent iteration. Interestingly, federated learning combines input from multiple residences to teach the neural network, thereby expanding the training set and improving the model's robustness and capacity for generalization [27]. Fig.3 shows the federated learning approach for assessment of vocational information literacy teaching ability.

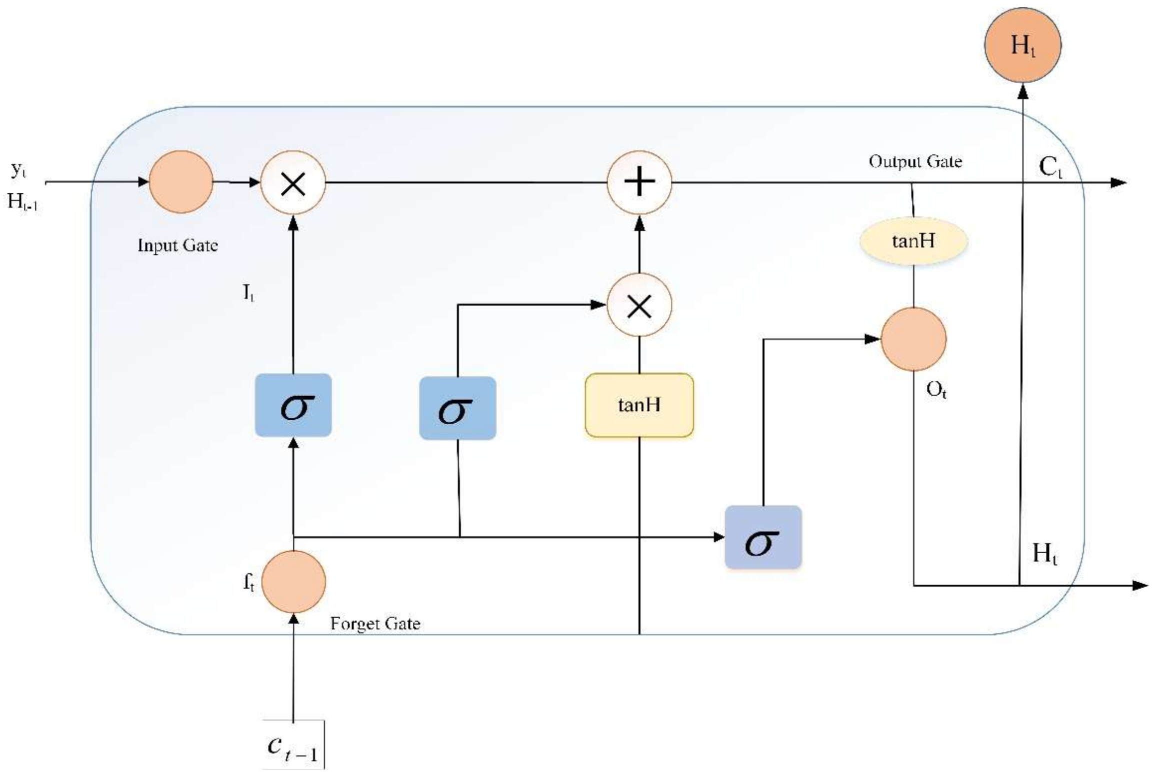

Fig. 2. LSTM Architecture

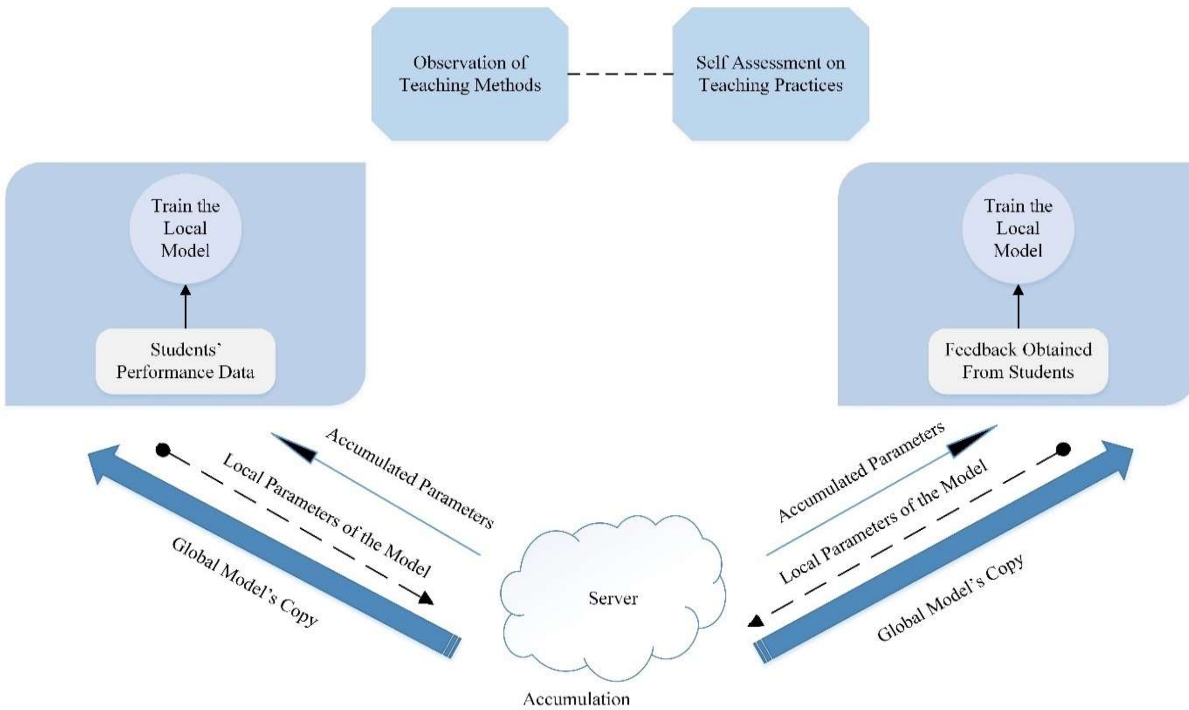

Fig. 3. Federated Learning For Assessment Of Vocational Information Literacy Teaching Ability

Machine learning (ML) for skill assessments in vocational education gathers literacy teaching skills from educational institutions into the centralized framework, and then uses that framework for training ML models. Federated Learning (FL), on the other hand, trains a ML algorithm locally on a variety of data users, such as decentralized nodes, and sends only the algorithm's changes back to the centralized server. Assume that data holders (k) $f_1, \dots \dots . f_k$ want to combine their individual data $d_1, \dots \dots . d_k$ for training only one ML model. A single framework is trained using $d = d_1, u \dots u. d_k$, in a centrally located technique that gathers all data in a single central location. When using federated learning, users of data $f_1, \dots \dots . f_k$ work together to train an algorithm $M_{federated}$ without exchanging information d_i with other information users, provided the overall federation's efficiency $\mathcal{P}_{federated}$ stays extremely near to that of the single centralized system $\mathcal{P}_{sum}$. This scenario is expressed as Eqn. (11).

$$\left|\mathcal{P}_{federated} - \mathcal{P}_{sum}\right| \leq \varphi \qquad (11)$$

Algorithm for Federated Learning Process

Input:

1. *Weights of global LSTM model*
2. *Students' performance data*
3. *Feedback obtained from students*
4. *Local data from data processing*

Output: *Trained global LSTM model for Vocational education skill assessment*

Step 1: *Initialize the global LSTM weights*
Step 2: *Training for every iteration*

- *Random subset selection*
- *Global model's copy sent to the selected devices*
- *Local data on every device is pre-processed*
- *Using the local data each device is trained*
  - *Utilizing stochastic gradient descent, the local model was updated for FedSGD*
  - *Utilizing averaging gradients, the local model was updated for FedAVG*
- *Updated model's variables are sent by the device to the server*

Step 3: *Received model's variables are aggregated by the server*
Step 4*: Repeat steps 1-3*
Until convergence standards are met
Step 5: *After step 4, the trained global model was sent to all contributors*
Step 6: *Expired local models are replaced with the updated global model*
Step 7: *Use the trained global model for vocational skill assessment*

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End

D. Fuzzy Rule-Based Vocational education skill Assessment

Following the extraction and classification of skills, the next step is to evaluate the skills or relevance of these capabilities inside the context of vocational education. Fuzzy rule-based structures are used to evaluate the obtained capabilities based on predefined standards and regulations. These rules may consider factors along with enterprise requirements, task necessities, and academic goals. Fuzzy inference rules are used to provide visible and configurable rule-based assessment. It specifically selects to apply the following rules: The term operator is IF is. Operators are skilled, for instance, IF the time that passed is skilled. Every statistic and level of expertise pair has a corresponding rule. Effectively, this means that for every skill class, they must specify a function of membership as well as a participation mechanism for every measure. In order for the collective membership across every class to equal one, next describe the ability class group membership functions to be symmetrical triangular values on the interval [0, 1].

By applying Gaussian, the estimation of kernel density to the training information, the metric function of membership for every skill category is experimentally calculated. The range of frequencies is estimated using Silverman's rule-of-thumb. Notably, every training session is able to contribute to several metric functions of membership with different weights and be a member of many skill categories. The output function of membership for every rule is calculated by clipping according to the number of members in the input functional. Finding the average of the highest of the output function membership is used for combining and defuzzify the collection of fuzzy rules. This open technique for evaluation is based on rules. The rules that were observed and their advantages are shown to the user. It has the capacity to determine the measures for which all connected fuzzy rules have the greatest net impact as useful feedback. When every metric has an advantageous net impact across all of the rules connected with it, that measure receives the "excellent" response. Fuzzy rules can be modified or eliminated, and the weights assigned to every rule can be changed to customize this approach. For increased accuracy, specialists might apply more complex rules based on their area of skills [28].

5. RESULTS AND DISCUSSION

In this research, the use of machine studying algorithms in the evaluation of vocational data literacy teaching capacity are discussed. The outcomes reveal promising consequences in enhancing the evaluation technique and imparting wise assistance to vocational educators. The utilization of machine learning algorithms enabled the improvement of robust evaluation models able to correctly comparing vocational data literacy teaching capacity. These models leverage advanced techniques to investigate different data, inclusive of instructional methods, student interactions, and educational substances, thereby offering complete insights into educators' performance. The incorporation of intelligence assistance features empowered educators with valuable remarks and hints for enhancing their teaching practices. By leveraging machine learning algorithms, the system can discover area of strengths and weaknesses in teaching capacity, presenting personalised tips for expert development and enhancement.

A. Comparison of Fed-LSTM's Efficiency with and Without SMOTE

Table I and Fig.4 illustrates the performance assessment of the proposed Federated LSTM model throughout exclusive iterations with and without SMOTE statistics processing. Incorporating SMOTE noticeably enhances the accuracy of the version, specially glaring inside the preliminary iterations wherein the magnificence imbalance trouble is greater stated. However, because the quantity of iterations will increase, the accuracy marginally decreases for each iteration, suggesting a capacity saturation factor in version performance. Efficiency, measured as the share difference among with and without SMOTE, demonstrates a constant development while SMOTE is applied, indicating that the enhanced accuracy is carried out with minor efficiency costs. Overall, the effects highlight the effectiveness of SMOTE in mitigating imbalance troubles and enhancing the overall performance of the Federated LSTM model, maintaining its application in addressing demanding situations associated with federated learning of in vocational ability extraction and classification.

Table I. Comparison Of Fed-Lstm's Efficiency With And Without Smote

Method	Iterations	Accuracy		Efficiency (%)
		With SMOTE	***Without SMOTE***	
Proposed Federated LSTM	1	99.4	96.7	2.7
	2	98.5	96.9	1.6
	3	97.3	95.6	1.7
	4	97.1	94.3	2.8
	5	92.8	90.2	2.6

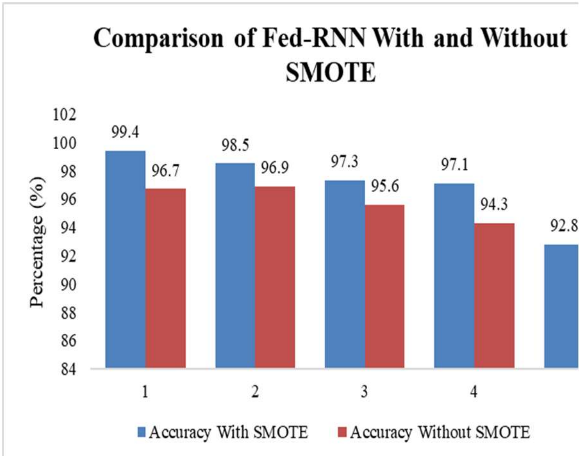

Fig. 4. Comparison of Fed-LSTM's Efficiency with and Without SMOTE

Training and Testing Accuracy of Fed-LSTM

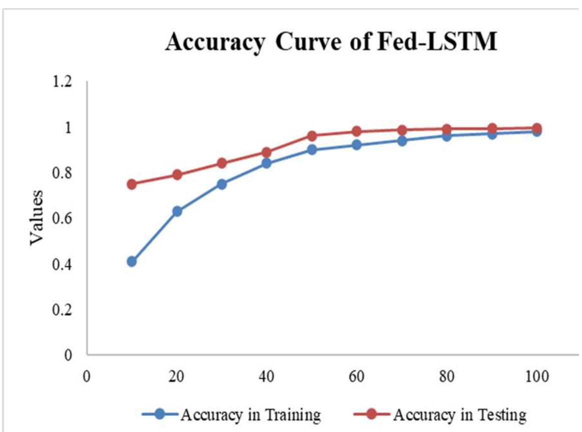

Fig. 5. Training and Testing Accuracy of Fed-LSTM

Fig. 5 depicting the training and testing accuracy of the Fed-LSTM model showcases its mastering performance over multiple iterations. Initially, at 10 iterations, each training and testing accuracies are low, indicating that the version remains within the early stages of learning and won't yet have captured the underlying patterns in the data efficiently. However, as the range of iterations will increase, both training and testing accuracies step by step improved, demonstrating the model's potential to examine and generalize from the data. Towards the end of the iterations, both training and testing accuracies approach excessive ranges, with the testing accuracy exceeding 99.4%, suggesting that the model has learned to appropriately classify times in the dataset. Overall, the graph illustrates the progressive improvement and generalization capacity of the Fed-LSTM model because it undergoes training iterations.

B. Training and Testing Loss of Fed-LSTM

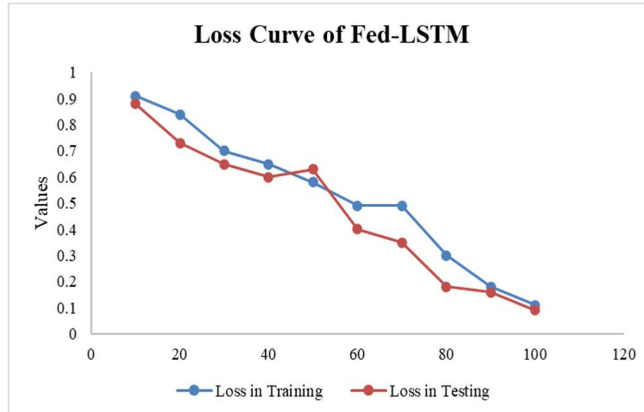

Fig. 6. Training and Testing Loss of Fed-LSTM

Fig. 6 depicting the training and testing loss of the Fed-LSTM model offers insights into its learning dynamics and generalization skills over multiple iterations. Initially, at 10 iterations, both training and testing losses are unpredictably excessive, indicating that the model's predictions deviate substantially from the real values. However, as the quantity of iterations increases, each training and testing losses progressively lower, demonstrating the model's improved ability to decrease mistakes and fit the statistics better. The gap between training and testing losses drops down progressively, suggesting that the model is efficiently generalizing to unseen data and avoid overfitting. Towards the iterations, both training and testing losses approach very low levels, with the trying out loss dropping lower 0.1, indicating that the version's predictions closely align with the actual values inside the dataset. Overall, the graph illustrates the progressive development and generalization potential of the Fed-LSTM model because it undergoes education iterations, highlighting its effectiveness in minimizing errors and correctly predicting outcomes.

C. Error Metrics

Table.2 and Fig.7 highlights the performance improvements done through the proposed Federated LSTM (Fed-LSTM) model over the conventional LSTM approach across the evaluation metrics. In terms of Mean Absolute Percentage Error (MAPE), the Fed-LSTM model outperforms the LSTM model notably, decreasing the error from 19.31 to11.34. Similarly, in Mean Absolute Error (MAE), the Fed-LSTM model achieves a great reduction from 3.67 to 0.452, indicating its ability to make more correct predictions with smaller deviations from the real values.

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Table II. Comparison Of Error Metrics

Methods	MAPE	MAE	RMSE
LSTM [29]	19.31	3.67	0.63
Proposed Fed-LSTM	11.34	0.452	0.174

The Root Mean Square Error (RMSE), the Fed-LSTM model demonstrates superior overall performance, reducing the error from 0.63 to 0.174, indicating its capability to decrease the sharpened differences between predicted and real values successfully. Overall, the evaluation underscores the efficacy of the proposed Fed-LSTM version in enhancing predictive accuracy and reducing mistakes compared to the traditional LSTM approach, thereby showcasing its ability for improving forecasting duties.

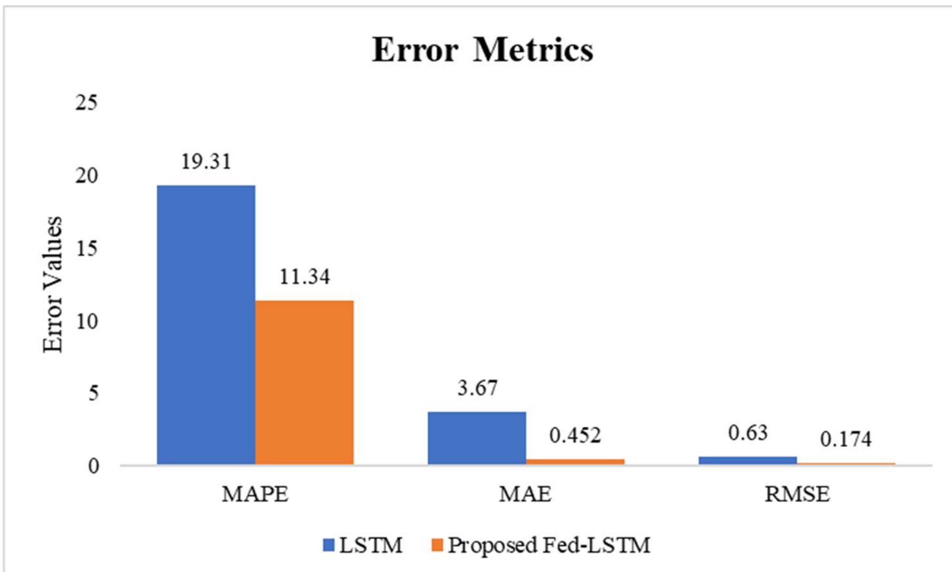

Fig. 7. Comparison Of Error Metrics

D. Performance Evaluation

Table III and Fig.8 highlights the significant overall performance enhancements performed by the proposed Federated LSTM (Fed-LSTM) model over the traditional LSTM method across various assessment metrics. In terms of accuracy, the Fed-LSTM version substantially outperforms the LSTM model, accomplishing an accuracy of 99.4% in comparison to 76.98% for LSTM, indicating its advanced capability to effectively classify instances. Moreover, the Fed-LSTM model shows higher precision (98.9% compared to 79.8%) and (99.1% as compared to 78.8%) values, suggesting that it could successfully perceive relevant times whilst minimizing false positives and fake negatives. The Fed-LSTM model achieves a substantially higher F1 score (99.32% in comparison to 78.9%), suggesting a higher balance between precision and recall.

Table III. Comparison Of Performance Metrics

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1 score (%)
LSTM [29]	76.98	79.8	78.8	78.9
Proposed Fed-LSTM	99.4	98.9	99.1	99.32

Overall, the comparison underscores the significant performance gains of the Fed-LSTM model in terms of accuracy, precision, drecall, and F1 score, highlighting its effectiveness in classification compared to the conventional LSTM method.

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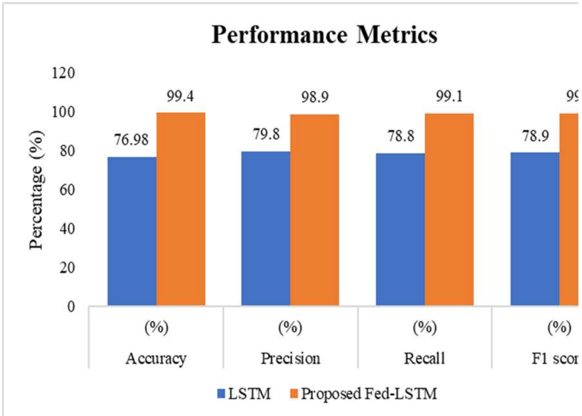

Fig. 8. Comparison Of Performance Metrics

E. Discussion

The results from the research exhibit the effectiveness and overall performance upgrades accomplished by means of the proposed Federated LSTM (Fed-LSTM) model as compared to traditional LSTM processes. Firstly, the assessment of efficiency with and without SMOTE demonstrates the sizable effect of SMOTE data processing in enhancing the accuracy of the Fed-LSTM model, specifically apparent in the initial iterations. Despite a minor decrease in accuracy with successive iterations, SMOTE always improves efficiency, indicating its effectiveness in addressing elegance imbalance problems and improving model performance. The assessment of training and testing accuracy similarly highlights the Fed-LSTM model's learning skills, with each accuracies step by step improving over iterations. The model demonstrates high level of accuracy, with testing accuracy exceeding 99.4% in the direction of the end of the iterations, indicating its ability to generalize well to unseen data and effectively classify instances in the dataset.

The evaluation of training and testing loss exhibits the Fed-LSTM model's ability to reduce mistakes in the data because the variety of iterations will increase. The version successfully generalizes to unseen data, as evidenced through the convergence of training and trying out losses towards very low ranges, indicating its effectiveness in minimizing errors and as it should be predicting outcomes. The evaluation of error metrics and performance evaluation metrics showcases extensive enhancements completed by the Fed-LSTM model over conventional LSTM techniques. The Fed-LSTM version continually outperforms in terms of accuracy, precision, recall, F1 rating, mean absolute percentage errors (MAPE), Mean absolute Errors (MAE), and Root Mean Square Error (RMSE), highlighting its advanced overall performance in type responsibilities [29]. The results underscore the efficacy and effectiveness of the proposed Fed-LSTM model in addressing demanding circumstances related to vocational ability extraction and type, showcasing its potential for enhancing forecasting responsibilities and enhancing vocational training skill evaluation approaches.

6. CONCLUSION AND FUTURE WORK

This study has contributed novel insights into the realm of vocational education skill assessment by leveraging machine learning techniques, particularly through the integration of SMOTE data processing and Fed-LSTM. By addressing class imbalance issues and improving the accuracy of skill assessment models, this research offers a pioneering approach to identifying learners' readiness and proficiency in non-technical skills. The utilization of the O*NET dataset and federated learning strategies further enhances the robustness and scalability of the proposed methodology. The findings underscore the potential of machine learning to revolutionize vocational education by providing granular insights and personalized assistance tailored to individual learners' needs. Moreover, the implications of this work extend beyond academia, with significant impacts on educational practices, policymaking, and workforce development initiatives. By improving the effectiveness of skill assessment in vocational settings, this research lays the groundwork for fostering a more skilled and competent workforce, thereby contributing to socioeconomic advancement and fostering lifelong learning opportunities for individuals worldwide. Overall, the novelty and impact of this work lie in its ability to bridge the gap between traditional assessment methods and the evolving demands of vocational education in the digital age.

The research conducted on the application of machine learning algorithms inside the evaluation of vocational information literacy teaching ability has achieved better findings and implications. The study introduced the Federated LSTM (Fed-LSTM) model and verified its effectiveness in improving vocational education talent assessment processes. Through a series of experiments and evaluation, it changed into observed that the Fed-LSTM model outperformed conventional LSTM approaches in phrases of accuracy, efficiency, and errors metrics. The incorporation of SMOTE data processing considerably improved the accuracy of the model, highlighting its capacity to mitigate class imbalance difficulties and improve model performance. Additionally, the Fed-LSTM model demonstrated strong learning abilities, with training and testing accuracies continuously enhancing over iterations.

The evaluation of schooling and checking out loss similarly emphasized the model's ability to limit errors and generalize properly to unseen information. The comparison of overall performance assessment metrics underscored the advanced performance of the Fed-LSTM model in classification tasks, showcasing its capacity for enhancing forecasting responsibilities and vocational education talent assessment strategies. Overall, the study's findings recommend that the utility of machine learning algorithms, especially the Fed-LSTM model, holds capacity for enhancing vocational education practices with the aid of supplying smart assistance to educators and enhancing the assessment of vocational data literacy coaching capability. These insights can inform future studies and the development of innovative procedures to vocational schooling and talent assessment.

Future work from this may explore several avenues to in addition develop the software of machine learning algorithms in vocational education ability evaluation. Firstly, studies should awareness on refining and optimizing the Fed-LSTM model to enhance its overall performance and scalability, especially in dealing with large datasets and accommodating extra complex vocational talent extraction works. Additionally, investigations into the mixing of other superior strategies, together with deep learning architectures or reinforcement learning algorithms, may offer new insights and strategies to enhance the accuracy and performance of vocational education talent assessment procedures. Moreover, exploring the utility of machine learning in personalised mastering and adaptive instruction ought to allow the development of personalized instructional reviews that cater to individual learner desires and choices. Finally, collaborative efforts among researchers, educators, and enterprise stakeholders could facilitate the development of practical tools and solutions that effectively leverage machine learning to assist vocational training and education tasks.

REFERENCES

[1] H. B. Lund and A. Karlsen, “The importance of vocational education institutions in manufacturing regions: adding content to a broad definition of regional innovation systems,” *Industry and Innovation*, vol. 27, no. 6, pp. 660–679, Jul. 2020, doi: 10.1080/13662716.2019.1616534.

[2] I. Onishchuk *et al.*, “Characteristics of Foreign Language Education in Foreign Countries and Ways of Applying Foreign Experience in Pedagogical Universities of Ukraine,” *Revista Romaneasca pentru Educatie Multidimensionala*, vol. 12, no. 3, Art. no. 3, Oct. 2020, doi: 10.18662/rrem/12.3/308.

[3] N. V. Antonova, Z. N. Shmeleva, and N. S. Kozulina, “Lifelong learning as the way of modern personality development in Russia on the example of higher educational institution of technical and natural-scientific profile,” *J. Phys.: Conf. Ser.*, vol. 1691, no. 1, p. 012146, Nov. 2020, doi: 10.1088/1742-6596/1691/1/012146.

[4] U. Venesaar, E. Malleus, G. Arro, and M. Toding, “Entrepreneurship Competence Model for Supporting Learners Development at All Educational Levels,” *Administrative Sciences*, vol. 12, no. 1, Art. no. 1, Mar. 2022, doi: 10.3390/admsci12010002.

[5] S. K. Gill, A. Dhir, G. Singh, and D. Vrontis, “Transformative Quality in Higher Education Institutions (HEIs): Conceptualisation, scale development and validation,” *Journal of Business Research*, vol. 138, pp. 275–286, Jan. 2022, doi: 10.1016/j.jbusres.2021.09.029.

[6] A. Verma, P. Purohit, T. Thornton, and K. Lamsal, “An examination of skill requirements for augmented reality and virtual reality job advertisements,” *Industry and Higher Education*, vol. 37, no. 1, pp. 46–57, Feb. 2023, doi: 10.1177/09504222221109104.

[7] K. Syauqi, S. Munadi, and M. B. Triyono, “Students’ Perceptions toward Vocational Education on Online Learning during the COVID-19 Pandemic,” *International Journal of Evaluation and Research in Education*, vol. 9, no. 4, pp. 881–886, Dec. 2020.

[8] C. Hofmeister and M. Pilz, “Using E-Learning to Deliver In-Service Teacher Training in the Vocational Education Sector: Perception and Acceptance in Poland, Italy and Germany,” *Education Sciences*, vol. 10, no. 7, Art. no. 7, Jul. 2020, doi: 10.3390/educsci10070182.

[9] S. Hoidn and V. Šťastný, “Labour Market Success of Initial Vocational Education and Training Graduates: A Comparative Study of Three Education Systems in Central Europe,” *Journal of Vocational Education & Training*, vol. 75, no. 4, pp. 629–653, Aug. 2023, doi: 10.1080/13636820.2021.1931946.

[10] V. Aarkrog, “The standing and status of vocational education and training in Denmark,” *Journal of Vocational Education & Training*, vol. 72, no. 2, pp. 170–188, Apr. 2020, doi: 10.1080/13636820.2020.1717586.

[11] I. Calero López and B. Rodríguez-López, “The relevance of transversal competences in

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

vocational education and training: a bibliometric analysis," *Empirical Res Voc Ed Train*, vol. 12, no. 1, p. 12, Nov. 2020, doi: 10.1186/s40461-020-00100-0.

[12] N. F. Amin, A. A. Latif, M. Arsat, N. Suhairom, N. F. Jumaat, and M. E. Ismail, "The Implementation of the Internship as a Coursework in Teaching and Learning Vocational Education," *Journal of Technical Education and Training*, vol. 12, no. 1, Art. no. 1, Jan. 2020, Accessed: Feb. 13, 2024. [Online]. Available: https://penerbit.uthm.edu.my/ojs/index.php/JTET/article/view/3290

[13] E. Schmid and V. Garrels, "Parental involvement and educational success among vulnerable students in vocational education and training," *Educational Research*, vol. 63, no. 4, pp. 456–473, Oct. 2021, doi: 10.1080/00131881.2021.1988672.

[14] L. Windelband, "Artificial Intelligence and Assistance Systems for Technical Vocational Education and Training – Opportunities and Risks," in *New Digital Work: Digital Sovereignty at the Workplace*, A. Shajek and E. A. Hartmann, Eds., Cham: Springer International Publishing, 2023, pp. 195–213. doi: 10.1007/978-3-031-26490-0_12.

[15] Suharno, N. A. Pambudi, and B. Harjanto, "Vocational education in Indonesia: History, development, opportunities, and challenges," *Children and Youth Services Review*, vol. 115, p. 105092, Aug. 2020, doi: 10.1016/j.childyouth.2020.105092.

[16] N. Bano, S. Yang, and E. Alam, "Emerging Challenges in Technical Vocational Education and Training of Pakistan in the Context of CPEC," *Economies*, vol. 10, no. 7, Art. no. 7, Jul. 2022, doi: 10.3390/economies10070153.

[17] V. I. Kovalchuk, S. V. Maslich, L. G. Movchan, V. V. Soroka, S. H. Lytvynova, and O. H. Kuzminska, "Digital transformation of vocational schools: problem analysis," in *CTE Workshop Proceedings*, 2022, pp. 107–123.

[18] F. Mutohhari, S. Sutiman, M. Nurtanto, N. Kholifah, and A. Samsudin, "Difficulties in implementing 21st century skills competence in vocational education learning," *IJERE*, vol. 10, no. 4, p. 1229, Dec. 2021, doi: 10.11591/ijere.v10i4.22028.

[19] F. Peng, S. Wang, and T. Yan, "Enhancing Vocational Education through Innovative Skills Competitions: Challenges and Solutions," *Journal of Contemporary Educational Research*, vol. 7, no. 7, Art. no. 7, Jul. 2023, doi: 10.26689/jcer.v7i7.5071.

[20] M. P. Ilić, D. Păun, N. Popović Šević, A. Hadžić, and A. Jianu, "Needs and Performance Analysis for Changes in Higher Education and Implementation of Artificial Intelligence, Machine Learning, and Extended Reality," *Education Sciences*, vol. 11, no. 10, Art. no. 10, Oct. 2021, doi: 10.3390/educsci11100568.

[21] Y. Shi, F. Peng, and F. Sun, "A Blended Learning Model Based on Smart Learning Environment to Improve College Students' Information Literacy," *IEEE Access*, vol. 10, pp. 89485–89498, 2022, doi: 10.1109/ACCESS.2022.3201105.

[22] H. Zhang, I. Lee, S. Ali, D. DiPaola, Y. Cheng, and C. Breazeal, "Integrating Ethics and Career Futures with Technical Learning to Promote AI Literacy for Middle School Students: An Exploratory Study," *Int J Artif Intell Educ*, vol. 33, no. 2, pp. 290–324, Jun. 2023, doi: 10.1007/s40593-022-00293-3.

[23] F. Chen, A. Sakyi, and Y. Cui, "Identifying Key Contextual Factors of Digital Reading Literacy Through a Machine Learning Approach," *Journal of Educational Computing Research*, vol. 60, no. 7, pp. 1763–1795, Dec. 2022, doi: 10.1177/07356331221083215.

[24] A. Hidalgo, S. Gabaly, G. Morales-Alonso, and A. Urueña, "The digital divide in light of sustainable development: An approach through advanced machine learning techniques," *Technological Forecasting and Social Change*, vol. 150, p. 119754, Jan. 2020, doi: 10.1016/j.techfore.2019.119754.

[25] A. José-García *et al.*, "C3-IoC: A Career Guidance System for Assessing Student Skills using Machine Learning and Network Visualisation," *Int J Artif Intell Educ*, vol. 33, no. 4, pp. 1092–1119, Dec. 2023, doi: 10.1007/s40593-022-00317-y.

[26] T. Kaewwiset, P. Temdee, and T. Yooyativong, "Employee Classification for Personalized Professional Training Using Machine Learning Techniques and SMOTE," in *2021 Joint International Conference on Digital Arts, Media and Technology with ECTI Northern Section Conference on Electrical, Electronics, Computer and Telecommunication Engineering*, Cha-am, Thailand: IEEE, Mar. 2021, pp. 376–379. doi: 10.1109/ECTIDAMTNCON51128.2021.9425754.

[27] Y. Shi and X. Xu, "Deep Federated Adaptation: An Adaptative Residential Load Forecasting

Approach with Federated Learning," *Sensors*, vol. 22, no. 9, p. 3264, Apr. 2022, doi: 10.3390/s22093264.

[28] M. S. Holden *et al.*, "Machine learning methods for automated technical skills assessment with instructional feedback in ultrasound-guided interventions," *Int J CARS*, vol. 14, no. 11, pp. 1993–2003, Nov. 2019, doi: 10.1007/s11548-019-01977-3.

[29] M. N. Fekri, K. Grolinger, and S. Mir, "Distributed load forecasting using smart meter data: Federated learning with Recurrent Neural Networks," *International Journal of Electrical Power & Energy Systems*, vol. 137, p. 107669, May 2022, doi: 10.1016/j.ijepes.2021.107669.