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CONSTRUCTION OF TEACHER LEARNING EVALUATION MODEL BASED ON DEEP LEARNING DATA MINING

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Abstract. In-class teaching assessment, which measures the effectiveness of teachers' instruction as well as how well students are learning in a classroom setting, is becoming more and more important in monitoring, and advancing the quality of education. As artificial intelligence (AI) advances quickly, the idea of intelligent instruction has gradually gotten better and progressively permeated every facet of educational application. The integration of artificial intelligence (AI) technology into the assessment of in-class instruction has grown into a research hotspot due to the prevalent role that classroom instruction plays in primary and undergraduate education. Modern educational systems aim to improve instruction effectiveness and customize learning opportunities for each student. In this paper, we provide a novel model for evaluating teacher learning that makes use of data mining and deep learning capabilities. The objective of the model is to analyse and interpret the intricate patterns present in educational data to offer a thorough evaluation of teacher effectiveness and student advancement. The model uses convolutional neural networks (CNNs) to mine large datasets, such as student comments, lesson plans, classroom interactions, and performance measures, to find important pedagogical indications that are associated with effective teaching outcomes. The effectiveness of the concept is confirmed in a range of educational contexts, indicating its scalability and flexibility. Its use in practical settings shows a notable increase in the accuracy of teacher assessments, offering a clear path forward for ongoing progress in education.

Key words: teacher learning evaluation, deep learning, data mining, artificial intelligence, teacher assessment

1. Introduction. Within the field of education, the assessment of students' educational achievement and their level of comprehension within the classroom are essential elements of academic quality management [3]. These measures have traditionally been measured using conventional methods that mostly depend on subjective evaluations and manual observation. But as artificial intelligence (AI) develops at a rapid pace and we enter the era of intelligent instruction, teaching and learning paradigms are changing dramatically.

Intelligent instruction is based on the idea that teaching should be examined and improved, in addition to using AI to make learning experiences better. In keeping with this, the incorporation of AI into in-class teaching assessments has become an important field of study, especially considering the crucial role that classroom instruction plays in determining student achievement in elementary and secondary education [15, 4]. These tests are designed to be more than just evaluation instruments; they are meant to be a tool for ongoing educational process development.

This research presents a novel model for evaluating teacher learning that is based on data mining and deep learning techniques to address the problem of evaluating teacher performance both objectively and qualitatively [9]. With the help of this model, which attempts to decipher the intricacies of educational data, meaningless data about teacher effectiveness and student progress can be meaningfully measured. Convolutional neural networks (CNNs), which carefully examine a variety of data sets, including student feedback, intricate lesson plans, complex classroom interactions, and empirical performance indicators, are at the heart of the model [18].

This all-encompassing method looks for important pedagogical indicators that are associated with excellent instruction. By doing this, the model hopes to support teachers in their professional development and evaluate them while also bringing their teaching practices into line with established success factors [13, 6]. The successful implementation of the suggested model in a variety of educational settings demonstrates its adaptability and resilience, highlighting its potential as a global instrument for raising teaching standards. By means of practical implementation and validation, the suggested approach highlights a noteworthy improvement in the accuracy of

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teacher evaluations, consequently charting a tactical course for ongoing educational improvement [20, 17]. The goal of this paper is to outline the design, operation, and consequences of this model to further the conversation about artificial intelligence's revolutionary potential for assessment and development in education.

The importance of in-class teaching assessments in raising the caliber of education has come to light more and more in recent years. These evaluations are essential for determining the degree of student learning occurring in classroom environments as well as the efficacy of teachers' guidance. The tremendous breakthroughs in artificial intelligence (AI) are changing the landscape of educational techniques just as we stand on the precipice of a technological revolution. AI-supported intelligent instruction is transforming the understanding, analysis, and improvement of educational processes.

A growing field of study is the use of AI into in-class teaching assessment, motivated by the significant influence that classroom instruction has on student learning outcomes at the primary and undergraduate levels. Through individualized learning experiences and optimized learning routes for students, this integration promises to improve assessment accuracy and efficacy. Our study presents a novel model that examines and decodes the intricate patterns contained in educational data by utilizing the powerful powers of data mining and deep learning.

The main contribution of proposed method is given below:

1. This research leverages the intersection of artificial intelligence and educational methods to present a transformative approach for in-class teaching assessment.
2. The study's main contribution is the creation of a sophisticated deep learning framework that mines educational information for the evaluation of learning outcomes and instructional efficacy using convolutional neural networks (CNNs).
3. The model guarantees the effective handling of high-dimensional data by utilizing CNNs, which translates into more precise, real-time assessments of instructional strategies.
4. Extensive validations in a variety of educational settings highlight the model's robustness and highlight its potential as a global standard for educational assessment.

The rest of our research article is written as follows: Section 2 discusses the related work on various solar energy potential, sky conditions and Deep Learning Algorithms. Section 3 shows the algorithm process and general working methodology of proposed work. Section 4 evaluates the implementation and results of the proposed method. Section 5 concludes the work and discusses the result evaluation.

2. Related Works. In the 1960s, American in-class researcher N.A. Flanders introduced the Flanders interaction analysis system (FIAS) [8], an in-class behavior analysis technology that is more thorough and sophisticated than the older speech act theory of in-class teacher-student interaction. FIAS is made up of a matrix table for data visualization, analysis, and research goals; a coding system to characterize classroom interactions; and a set of guidelines for observing and documenting codes. The modern era of in-class grading is just getting started [19, 7].

Flipped learning is defined as when students perform tasks that are typically completed outside of class (e.g., practicing problem-solving techniques) and then return to the classroom session [5]. In contrast, traditional classroom methods—which involve presenting and transmitting information through the teaching method—are typically completed outside of the classroom and typically occur prior to class. Statistics, idea visualization, classification, clustering with associative based analysis, anomaly identification, and text-based mining are all part of the data mining approach used in the education sector [16].

Creating a new Chinese language model that defies tradition and is not constrained by time or place is a significant problem that requires immediate attention considering the advancements in multimedia and network technologies [12]. Individuals have been investigating and attempting to apply new technologies and techniques to enhance teaching and learning methods and means to increase teaching efficiency and better train abilities [2]. In addition, we seek to implement differentiated education based on each student's unique learning foundation, learning style, and other attributes, while teaching them in accordance with their aptitude [11]. But it's been hard to teach every student based on their potential because of a lack of resources for teachers and demands on teaching effectiveness.

This objective can be achieved with the help of the Intelligent Teaching System (ITS) proposal. The time and distance limits of traditional education are overcome by current Internet-based education by establishing an

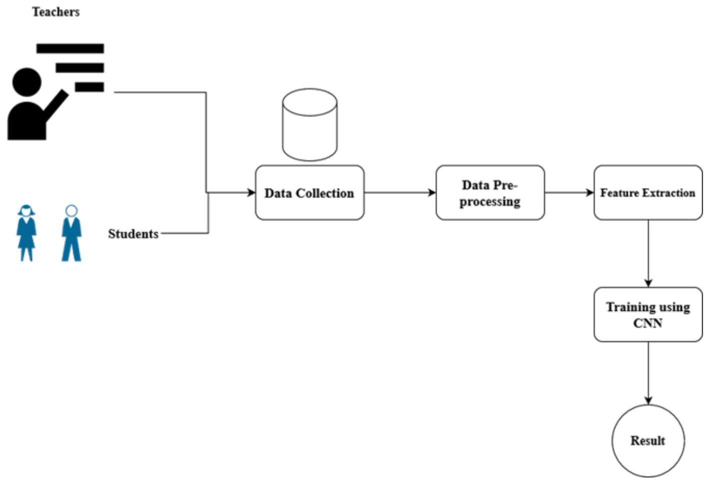

Fig. 3.1: Architecture of Proposed Method

open learning environment [1, 14]. It is essential for developing education, realizing logical resource allocation, and exploiting the resource advantages of diverse current education systems. It also provides a workable fix for the issue [10] To solve the limitations of the current network teaching system, this study develops and establishes an intelligent Chinese language network teaching system model.

Current models frequently mostly rely on textual data, including evaluations from students or the outcomes of standardized tests. The thorough integration of multimodal data sources—like audio, video, and interactive digital content—which are essential for developing a full knowledge of classroom dynamics and teacher-student interactions, is conspicuously lacking.

A lot of AI models concentrate on post-hoc examination of learning data, which reduces their usefulness for instantaneous instructional modification and real-time feedback. Real-time models that can give teachers and students immediate feedback are needed since they can greatly improve learning results.

3. Proposed Methodology. The proposed method for the Construction of teacher learning evaluation model based on CNN with equations data mining. Initially, the student feedback is collected and then the data is pre-processed. Next the data is extracted by using CNN and then the extracted features are trained by using CNN method. In figure 3.1 shows the architecture of proposed method.

The data sources are probably represented by these symbols. Instructors may offer lesson plans, instructional strategies, or assessments, while students may offer comments or performance indicators. At this point, information is gathered from the sources. It probably involves gathering a variety of data, including exam results, attendance records, student involvement, feedback, etc. The gathered data is currently being cleaned and transformed. Normalizing scores, encoding categorical variables, addressing missing values, and any other actions necessary to get the data ready for feature extraction are examples of pre-processing. Finding and extracting features from the pre-processed data that are pertinent to the learning job is the method involved in this procedure. Creating embeddings or spotting informative patterns or structures could be part of this in the context of CNNs.

A CNN model receives the features that were extracted in the preceding stage. Convolutional, pooling, and fully connected layers are the methods used by the CNN to learn from the features and modify its weights via backpropagation. The CNN model's training yielded the final output. This could be any kind of outcome that the model was trained to provide, including regression outputs like forecasting student performance or predictions like classifying teaching styles.

3.1. Data Collection and Pre-processing. Deep learning approaches are used to evaluate and interpret educational data in order to build a teacher learning evaluation model based on convolutional neural networks

(CNNs). The main elements of such a model are explained in this part, with an emphasis on the use of CNNs in the context of educational data mining for teacher assessment.

Data on education that is pertinent to the efficacy of instruction is gathered. Student assessments and feedback could be a part of this. Metrics of engagement and classroom interactions. Lesson plans and resources for teachers. Test results and grades are examples of student performance statistics. Preprocessing is done on this data to manage missing values, normalize scores, and transform qualitative input into a measurable manner. Textual data, such as feedback, is frequently transformed into numerical data using embedding and tokenization techniques.

3.2. Feature Extraction. CNNs are skilled at extracting features automatically. Word embeddings can be used to transform words into vector representations for textual input, which is subsequently fed into the CNN. Various encoding and normalizing methods are used to prepare numerical and categorical data so that a neural network can process it.

3.3. Training using CNN. These layers generate feature maps by filtering the input. Local dependencies, like word patterns in feedback or engagement data patterns, can be captured by them.

Convolutional Layers. Apply filters (kernels) to the input to create feature maps that summarize the presence of detected features in the input.

Activation Functions. Introduce non-linearities into the network, allowing it to learn complex patterns. The Rectified Linear Unit (ReLU) is a common choice for CNNs.

Pooling Layers. Reduce the dimensionality of the feature maps, making the detection of features invariant to scale and orientation.

Fully Connected Layers. These layers connect every neuron in one layer to every neuron in the next layer, making it possible to classify the image based on the features extracted by the convolutional and pooling layers.

Output Layer. Typically, a softmax activation function that converts the output of the network into probability distributions over predefined classes.

The convolution operation in the first layer can be represented as:

$$F_{ij}^{l} = \sigma(\sum_{m=0}^{M-1}\sum_{n=0}^{N-1} W_{mn}^{l} \cdot I_{(i+m)(j+n)} + b^{l}) \tag{3.1}$$

where F_{ij}^{l} is the feature map at location (i,j) in layer l. W_{mn}^{l} is the weight of the kernel at position (m,n) in layer l. $I_{(i+m)(j+n)}$ is the input image or feature map from the previous layer at the corresponding location. b^{l} is the bias term for layer l. σ represents the activation function, e.g., ReLU.

Pooling (e.g., max pooling) reduces the dimensionality:

$$P_{ij}^{l} = max(Area_{ij}^{l}) \tag{3.2}$$

where P_{ij}^{l} is the output of the pooling operation at location (i,j) in layer l. $Area_{ij}^{l}$represents the area of the feature map being pooled.

The fully connected layer can be represented as:

$$O_k = \sigma(\sum_{n} W_{kn}.F_n + b_k) \tag{3.3}$$

where O_k is the output for class k. W_{kn} is the weight connecting neuron n to output k. F_n is the flattened feature map input from the last convolutional or pooling layer. b_k is the bias term for output class k.

For classification, the softmax function is commonly used:

$$Softmax(O_k) = \frac{e^{o_k}}{\sum_j e^{o_j}} \tag{3.4}$$

where e^{o_k} is the exponential of the output for class k. The denominator is the sum of exponentials of all outputs, ensuring the output is a probability distribution.

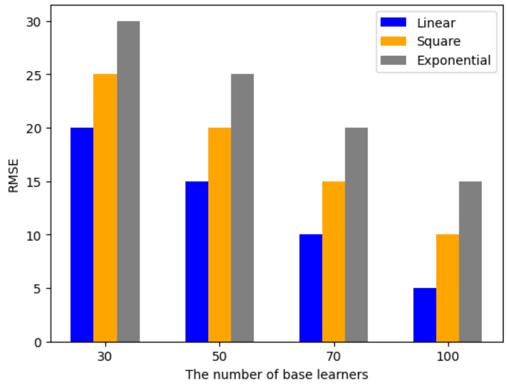

Fig. 4.1: Evaluation of RMSE based on Number of Base learners

4. Result Analysis. The information in our data set was taken from and organized within the resultant data set of four related research projects conducted by Hangzhou Hikvision Digital Technology Co., Ltd., China, our partner. These projects include: (1) ”Machine Vision-Based Video Recognition for In-Class Movement,” (2) ”Super Large- Scale Vocabulary Speech Recognition in Classrooms Situations,” (3) ”Voiceprint Recognition in Classroom Scenarios,” and (4) ”Far Field Pickup in Classroom Scenarios.” The primary data is from an actual smart learning environment implemented by Hangzhou Hikvision Digital Technology Co. There is a voice recognition pickup and two cameras in this intelligent classroom that record videos of the instructors and kids, accordingly [3].

To gather five different types of data, including student movement, student emotion, teacher movement, teacher emotion, teacher volume, and speech speed, as well as teacher speech text data for the entire class, 200 teacher samples and 300 student samples were chosen for the experiment. The audio and video data in the classroom were sampled every three seconds. The outcomes of the after-class tests are used to obtain the student label data, and the researchers' evaluation is used to obtain the teacher label data.

One can separate the input data into two categories: sequential information, which includes student motion, feelings, quantity, and velocity, and non-sequential data, which includes teachers' voice text. Calculating the average length of statistics and their frequency is necessary for sequence data. Furthermore, word frequency statistics must be performed for non-sequence data.

The Root Mean Square Error (RMSE) of ensemble models with varying numbers of base learners is shown in figure 4.1 as a bar chart. The discrepancy between values observed and values predicted by a model is measured by the Root Mean Square Error (RMSE). The bars are categorized into groups of 30, 50, 70, and 100 base learners based on the number of base learners in the models.

There are three sets of bars: linear, square, and exponential. These represent the various types of loss functions that are employed in statistical and machine learning models. There are four bars inside each group, each of which represents the RMSE for a particular parameter setting. The legend indicates which color corresponds to which parameter: yellow for 30, blue for 50, gray for 70, and orange for 100.These could be any hyperparameter that is adjusted during the model training process, such as learning rate, epochs, iterations, or the number of trees in a random forest. The RMSE values, a measurement of the average size of the errors between the values the model predicts and the observed values, are displayed on the y-axis. In figure 4.2 shows the result of RMSE and Loss Function.

The diagonal cells display the percentage of accurate predictions for each class, arranged from top left to bottom right. Usually, these numbers are normalized so that the total for each row is 1. In these diagonal cells, an ideal model would have 1.0 and zeros in the other cells. With a high normalized value of 0.93, ”Introduction” indicates that the model predicts this class accurately most of the time. With a rating of 0.78, ”Natural” is likewise quite high. With a diagonal value of 0.66, ”Interactive” has the lowest score, indicating that this class is the most difficult for the model to predict correctly. In the off-diagonal cells, the misclassification rates are

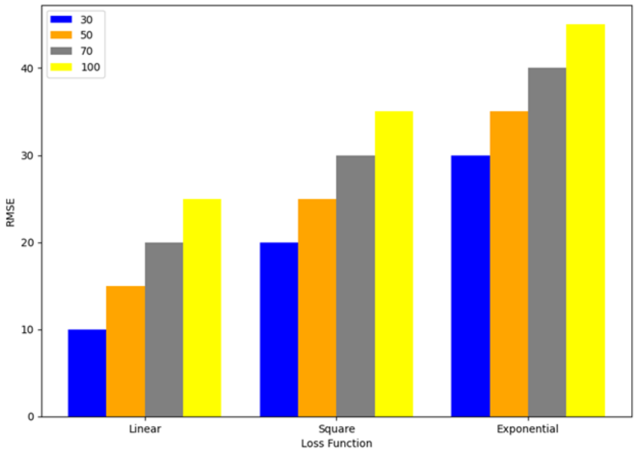

Fig. 4.2: RMSE and Loss Function

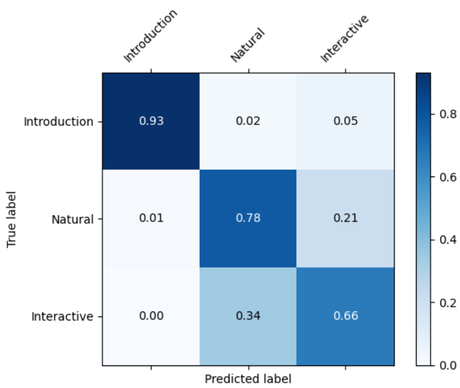

Fig. 4.3: Confusion matrix for Teachers Type

displayed. As an illustration, the word "Introduction" is occasionally mislabeled as "Natural" (0.02) or "Interactive" (0.05). 'Natural' is incorrectly categorized as 'Interactive' (0.21) or 'Introduction' (0.01). 'Introduction' classes are the most accurately predicted by the model, whilst 'Interactive' classes are less accurately predicted. 'Natural' and 'Interactive' classes are more frequently confused by the model with each other than 'Introduction' with any other class. In figure 4.3 shows the confusion matrix based on teachers type.

An instrument that makes it possible to visualize an algorithm's performance—usually supervised learning—is the confusion matrix. The projected class is represented by each column in the matrix, and the actual class is represented by each row. Predicted labels are displayed on the x-axis, while true labels are displayed on the y-axis. In this matrix, categories like "Passionate," "Numerous," and "Solemn" have both predicted and true labels. The normalized number of observations is represented by the color shade, which ranges from 0 to 1. Higher values are generally indicated by deeper hues. The normalized count of predictions for each true/predicted label pair is represented by the integers in the matrix. In the upper left corner, for instance, the number 0.92 signifies that 92% of the actual "Passionate" cases were accurately predicted to be "Passionate." In figure 4.4 shows the confusion matrix based on teachers style.

This is represented by a graph that indicates how well each model predicts the proper category for a given input. The y-axis measures this and ranges from roughly 0.65 to 0.95. The x-axis displays the following three categories (or tasks): "Teachers' Type," "Teachers' Style," and "Teachers' Media Usage." These could stand

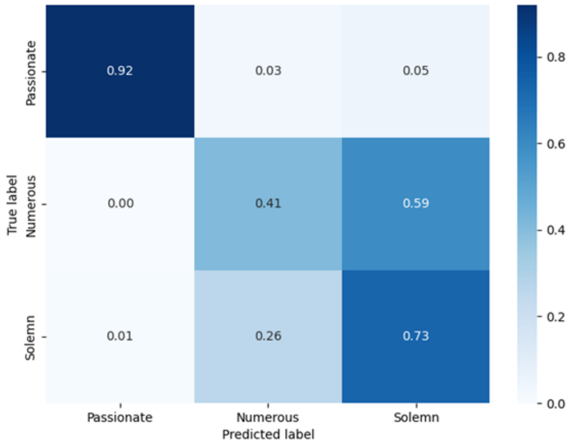

Fig. 4.4: Confusion matrix for Teachers Style

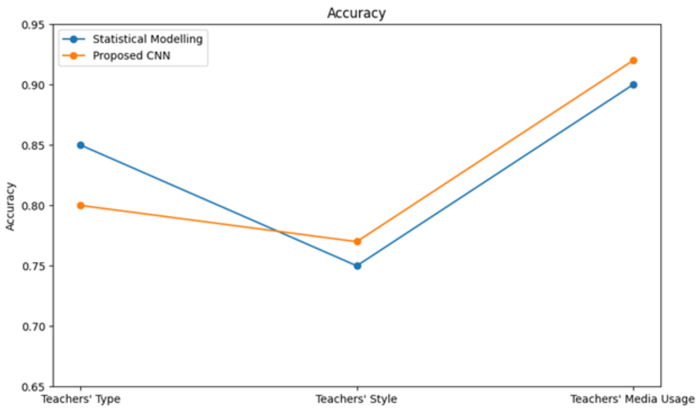

Fig. 4.5: Accuracy

in for the various facets of instruction that the models are attempting to categorize. The accuracy of each model on the three tasks is represented by the lines labeled "Statistical Modelling" (blue) and "Proposed CNN" (orange). The CNN marginally outperforms statistical modeling on "Teachers' Type," while both models perform similarly. Both models show a discernible decline in accuracy on "Teachers' Style," with the CNN showing a bigger decline. In figure 4.5 shows the result of Accuracy.

5. Conclusion. The importance of in-class teaching evaluation, which gauges how well students are learning in a classroom environment and how well teachers are instructing their classes, is growing as a means of tracking and improving educational standards. The concept of intelligent instruction has improved throughout time and permeated every aspect of educational application as artificial intelligence (AI) develops at a rapid rate. Because classroom instruction is so common in elementary and secondary education, the incorporation of artificial intelligence (AI) technology into the evaluation of in-class instruction has become a hotspot for research. The goals of contemporary educational systems are to increase the efficacy of instruction and personalize learning experiences for every student. In this research, we provide a novel approach that utilizes deep learning and data mining capabilities to assess teacher learning. The model's goal is to analyze and decipher the complex patterns seen in educational data in order to provide a comprehensive assessment of teacher effectiveness and student progress. In order to identify significant pedagogical indicators that are connected to successful teaching results, the model mines massive datasets, including student comments, lesson plans, classroom interactions, and performance measurements, using convolutional neural networks (CNNs). Numerous educational situations attest to the concept's efficacy, demonstrating its scalability and versatility. When used in real-world contexts, teacher assessments exhibit a discernible improvement in accuracy, providing a clear route forward for continuous educational advancement.

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