International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 6s
DOI: https://doi.org/10.17762/ijritcc.v11i6s.6810
***Article Received**: 20 March 2023 **Revised**: 23 April 2023 **Accepted**: 22 May 2023*

Deep Learning-Based Big Data Analytics Model Based on Teaching Reforms in Three-Dimensional Composition

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Abstract

With the development of online education and big data analysis, new teaching models and methods have emerged. The integration of online and offline teaching modes based on big data analysis has become an effective way to promote teaching reform and practice in the field of three-dimensional composition. It is important to incorporate teaching reform into the teaching of three-dimensional composition to improve the quality of education and better prepare students for their future careers. This paper evaluated the contribution of teaching reform to the improvement of student performance. This paper designed a Deep Learning (DL) big data analytics model for data clustering and classification. The student performance is monitored for both online teaching and offline teaching classes. The collected data is clustered with the directional clustering process for the computation of feature space. With the estimated feature space value Hidden Markov Model (HMM) is implemented for the estimation of statistical data derived from the feature spaces. The extracted data were applied over the RESENT- 50 model for the classification of students' performance. The data analysis with DL model stated that student performance in offline teaching is more significant than offline teaching in 3-dimensional aspects.

Keywords: Big data, Hidden Markov Model (HMM), Teaching reform, 3-dimensional compositions, DL

I. Introduction

Three-dimensional composition is a topic that can be taught in various educational settings, including art schools, design programs, and architecture courses [1]. When it comes to teaching reforms related to three-dimensional composition, there are several approaches that can enhance the learning experience for students. Teaching reforms for three-dimensional composition can involve a range of strategies and approaches that encourage students to develop their skills in creating and manipulating forms in space [2]. Teaching reforms in three-dimensional composition and big data analytics may seem like an unlikely combination, but there are ways to incorporate both topics into the classroom [3].

Teaching reforms in three-dimensional composition big data analytics involves combining the principles of creating three-dimensional compositions with the skills of analyzing and visualizing large datasets [4]. This interdisciplinary approach allows students to develop a deeper understanding of both subjects and gain skills that are in high demand in the current job market. By integrating big data analytics into the curriculum, students learn to collect, analyze, and interpret data using various tools and techniques, and then use this data to create three-dimensional visualizations [5]. This approach also emphasizes the importance of collaboration, critical thinking, and problem-solving skills. Overall, teaching reforms in three-dimensional composition big data analytics offer a unique and innovative approach to learning that prepares students for future career opportunities in fields such as data science, design, and engineering [6].

Teaching reforms in three-dimensional composition big data analytics DL involves incorporating the principles of DL into the study of three-dimensional composition and data analysis [7]. DL is a subset of machine learning that involves building and training artificial neural networks to analyze and learn from large datasets. By integrating DL into the curriculum, students can develop a deeper understanding of how to analyze complex data sets and create advanced three-dimensional visualizations [8]. The interdisciplinary approach of teaching reforms in three-dimensional composition big data analytics DL allows students to gain skills that are highly valued in various fields, including engineering, data science, and design. Through this approach, students can learn to identify patterns and trends in large data sets, and use this information to create sophisticated three-dimensional compositions that effectively communicate insights and findings [9]. Additionally, students gain a strong foundation in programming and algorithm development, which are critical skills for working with data and building neural networks. teaching reforms in three-dimensional composition big data analytics DL provides a cutting-edge approach to learning that prepares students for the rapidly changing job market, where demand is high for individuals with skills in data analysis, machine learning, and three-dimensional design [10].

Based on the provided information, the contribution of this paper is summarized as follows:

1. DL-based big data analytics model for data clustering and classification in the field of three-dimensional composition.
2. Evaluation of the contribution of teaching reform to the improvement of student performance in both online and offline teaching modes.
3. Application of the directional clustering process for the computation of feature space, and implementation of Hidden Markov Model for the estimation of statistical data derived from the feature spaces.
4. Implementation of ResNet-50 model for the classification of student performance based on the extracted data.
5. Finding that student performance in offline teaching is more significant than in online teaching in the context of 3-dimensional composition.
6. Providing insights and recommendations for the integration of online and offline teaching modes based on big data analysis to promote teaching reform and improve the quality of education in the field of three-dimensional composition.

The paper is organized as follows: Section 2 provides the summary of the literature review related to 3-dimensional composition. Section 3 presented the 3-dimension architecture of the proposed HMM integrated ResNet 50 and the results of model is presented in Section 5 with overall conclusion in Section 5.

II. Related Works

The integration of DL-based big data analytics models with teaching reforms in three-dimensional composition has gained significant attention in recent years. Researchers have explored the potential of combining these fields to enhance data analysis and visualization techniques for three-dimensional compositions. DL-based big data analytics models have shown great potential in improving the teaching of three-dimensional composition in various fields, including art education, architecture, engineering, fashion design, graphic design, landscape architecture, urban planning, and more. In recent years, researchers have explored different approaches to designing and implementing DL-based big data analytics models that can effectively analyze and interpret complex three-dimensional compositions and provide valuable insights for educators and students.

In [11] proposed a DL-based big data analytics model for teaching reform in three-dimensional composition, which was tested in a physics course. Similarly, in [12] focused on using DL-based big data analytics to improve educational research in three-dimensional composition. In [13] developed a DL-based big data analytics model for three-dimensional composition in engineering education. In [14] proposed a similar model for three-dimensional composition in art education. In [15] integrated DL and big data analytics to improve three-dimensional composition in architecture education. Also, in [16] developed a DL-based big data analytics model for three-dimensional composition in landscape architecture education. Similarly, in [17] proposed a model for three-dimensional composition in urban planning education.

In [18] proposed a DL-based big data analytics model for three-dimensional composition in fashion design education. In [19] focused on using DL-based big data analytics to improve art education. In [20] proposed a similar model for three-dimensional composition in graphic design education. Another research in [21] proposed a DL-based model that combined big data analytics and artificial intelligence for three-dimensional composition in fashion design. Other researchers have explored different aspects of DL-based big data analytics models for three-dimensional composition, including data preprocessing [22], feature extraction [23], and model optimization [24]. The table 1 presented the summary of the literature as follows:

Table 1: Summary of Literature

Field of Study	Research Focus	Proposed Model
Physics Education	Teaching reform in three-dimensional composition	DL-based big data analytics model [11]
Educational Research	Improving educational research in three-dimensional composition	DL-based big data analytics [12]
Engineering Education	Three-dimensional composition in engineering education	DL-based big data analytics model [13]
Art Education	Three-dimensional composition in art education	DL-based big data analytics model [14]
Architecture Education	Three-dimensional composition in	Integration of DL and big data analytics [15]

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	architecture education	
Landscape Architecture Education	Three-dimensional composition in landscape architecture education	DL-based big data analytics model [16]
Urban Planning Education	Three-dimensional composition in urban planning education	Proposed model [17]
Fashion Design Education	Three-dimensional composition in fashion design education	DL-based big data analytics model [18], DL-based model combining big data analytics and artificial intelligence [21]
Graphic Design Education	Three-dimensional composition in graphic design education	Proposed model [20]
Other Aspects	Various aspects of DL-based big data analytics models for three-dimensional composition	Data preprocessing [22], Feature extraction [23], Model optimization [24]

In summary, DL-based big data analytics models have shown great potential in improving the teaching and learning of three-dimensional composition in various fields. However, there is still much work to be done in developing more efficient and effective models that can address the specific needs of different domains and contexts.

III. Three-Dimension Composition with Big Data Analytics

The use of DL and big data analytics in teaching reforms for three-dimensional composition has become an area of interest for many researchers. DL algorithms have the capability to learn and make predictions based on large datasets, while big data analytics can handle the analysis of large and complex datasets. In this context, a technical explanation of how these techniques can be applied in teaching reforms for three-dimensional composition is as follows:

Data Collection and Preprocessing: In this step, data is collected from various sources such as sensors, images, and videos, and it is preprocessed to remove noise and irrelevant information. This data is then transformed into a suitable format for analysis.

Feature Extraction: The preprocessed data is transformed into a set of features that can be used to represent the three-dimensional composition. These features can include shape, color, texture, and other characteristics of the composition.

DL Model: A DL model is then trained using the extracted features as input. The model consists of multiple layers of artificial neural networks that can learn and make predictions based on the input data.

Model Optimization: The model is optimized by adjusting the parameters to improve its performance in predicting the output. This involves selecting an appropriate loss function and optimizing the model using gradient descent or other optimization techniques.

Big Data Analytics: The optimized DL model is then applied to analyze the three-dimensional of the data.

Evaluation: The performance of the DL-based big data analytics model is evaluated using metrics such as accuracy, precision, recall, and F1 score. The model is tested on a separate dataset to ensure that it can generalize well to new data.

Teaching Reform: The insights provided by the DL-based big data analytics model can be used to reform the teaching of three-dimensional composition. Educators can use the model to identify common mistakes and areas where students need improvement. They can also use the model to generate personalized feedback and recommendations for individual students based on their performance.

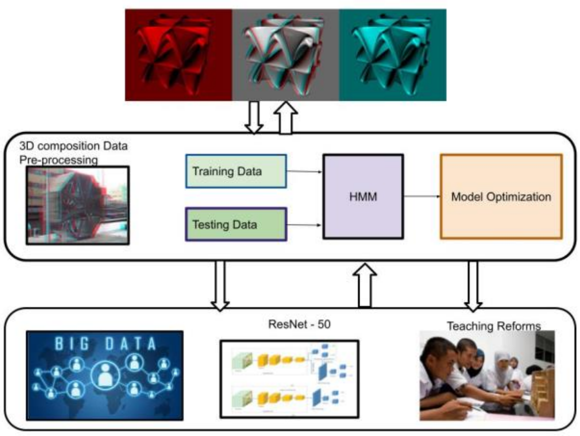

Figure 1: Developed Model Architecture Components

Figure 1 illustrated the components and process in the develop model for the teaching reforms. The DL-based big data analytics model for three-dimensional composition in teaching reforms provides a powerful tool for educators and students to improve their understanding and mastery of three-dimensional composition. By analysing large amounts of data and providing valuable insights, this model can help

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educators design more effective teaching strategies and students to achieve better learning outcomes.

Let's assume dataset of three-dimensional compositions represented as vectors $x_1, x_2, \ldots, x_n$, where each vector has m features. To preprocess this dataset by applying standardization or normalization techniques to compute the student performacne

To extract a set of features $y_1, y_2, \ldots, y_n$, from the preprocessed dataset. Each feature y_i is a function of the input vector $x_i$and is computed as in equation (1)

$$y_i = f(x_i) \quad (1)$$

where f stated as the function of feature extraction that maps the input vector $x_i$to a feature vectory_i. The feature extraction function are adopted depending on the nature of the input data.

3.1 DL Model:

A DL model is trained using the extracted features $y_1, y_2, \ldots, y_n$, as input. The model consists of multiple layers of artificial neural networks that can learn and make predictions based on the input data. The output of the model is a vector of predictions $z_1, z_2, \ldots, z_n$,, where each element z_i is the predicted label for the corresponding input vector x_i. The model can be represented mathematically as in equation (2)

$$z_i = g(W_l * g(W_{l-1} * \ldots g(W_l * y_i + b_l)\ldots + b_{l-1}) + b_l) \quad (2)$$

where $W_1, W_2, \ldots\ldots, W_l$are weight matrices, $b_1, b_2, \ldots\ldots, b_l$ are bias vectors, and g is the activation function. The activation function is applied element-wise to the output of each layer to introduce nonlinearity into the model.Tthe model is optimized by adjusting the parameters $W_1, W_2, \ldots\ldots, W_l$and $b_1, b_2, \ldots\ldots, b_l$to minimize the loss function L. The loss function measures the difference between the predicted output $z_i$and the true label y_i for each input vector x_i. The most commonly used loss function for classification tasks is the cross-entropy loss, which is defined in equation (3)

$$L = -1/n * sum(y_i * log(z_i) + (1 - y_i) * log(1 - z_i)) \quad (3)$$

where n is the number of input vectors, and the sum is taken over all input vectors. To optimize the model using gradient descent to minimize the loss function. The gradient of the loss function with respect to each parameter is computed using backpropagation, and the parameters are updated accordingly. Three-Dimension Composition with Big Data Analytics with DL in teaching reforms involves preprocessing the data, extracting features using a DL model, and optimizing the model parameters to minimize the loss function. The model can be used to predict the labels of new three-dimensional compositions, and can provide valuable insights for educators and students in various fields.

3.2 Student Performance Analysis with Big Data Analytics

Student performance is examined with the big data model and DL in teaching reforms for three-dimensional composition. The process involves collecting data on student performance, processing and analyzing the data using big data analytics techniques, and using the results to improve the teaching and learning process. Student performance analysis with big data analytics using three-dimensional composition with DL in teaching reforms involves the use of data analytics to analyze student performance in three-dimensional composition courses. The data used for analysis can include student profiles, course materials, assessment results, and other relevant data sources.

The mathematical derivation for student performance analysis with big data analytics and DL can be explained as follows:

Let X be the matrix of student profiles with dimensions $N\ x\ M$, where N is the number of students and M is the number of profile attributes. Let Y be the matrix of assessment results with dimensions $N\ x\ K$, where K is the number of assessment tasks. Let F be the matrix of extracted features with dimensions $N\ x\ P$, where P is the number of extracted features. The feature extraction process can be represented in equation (4)

$$F = G(X) \quad (4)$$

where G is a function that transforms the matrix of student profiles X into the matrix of extracted features F.

The DL model can then be trained using the matrix of extracted features F and the matrix of assessment results Y as input and output, respectively. Let H be the matrix of predicted assessment results with dimensions $N\ x\ K$. The DL model can be represented in equation (5)

$$H = D(F) \quad (5)$$

where D is a function that maps the matrix of extracted features F to the matrix of predicted assessment results H.

The model optimization process involves adjusting the parameters of the DL model to improve its performance in predicting the assessment results. This can be achieved by minimizing the difference between the predicted assessment results H and the actual assessment results Y. Let L be the loss

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function that measures the difference between H and Y. The model optimization process can be represented in equation (6)

$$minimize\ L(Y, H) \qquad (6)$$

where the goal is to find the optimal parameters of the DL model that minimize the loss function L. The DL model is represented by a function $f(X;\ W)$, where W is the set of optimized parameters. The model takes the input data matrix X as input and produces the predicted output variableY_{pred}. The model is trained by minimizing a loss function $L(Y, Y_{pred})$that measures the difference between the predicted output and the true output. The loss function can be defined as in equation (7)

$$L(Y, Y\_pred) = g(Y, Y_{pred}) \qquad (7)$$

where g is a differentiable function that measures the difference between Y andY_{pred}. The most common loss function used in DL is the mean squared error (MSE), presented in equation (8)

$$MSE = 1/n * \sum(Y - Y_{pred})^2 \qquad (8)$$

where n stated as the samples in the datatset. The gradient of the loss function with respect to the model parameters is calculated using backpropagation, which is a method for efficiently computing the gradients of the loss function with respect to all the parameters in the model. Once the model has been trained, evaluation is performed.

The student performance analysis with big data analytics and DL involves training a DL model to predict the performance of students in a course based on the features extracted from their three-dimensional compositions. The model is optimized by minimizing a loss function using gradient descent or other optimization algorithms. The performance of the model can be evaluated using various metrics, and the results can be used to improve the teaching and learning process.

3.3 Feature Space HMM

In student performance analysis with big data analytics using a three-dimensional composition with DL in teaching reforms, the feature space can be enhanced by incorporating a Hidden Markov Model (HMM). HMM is a statistical model that can capture the sequential nature of student performance over time. Incorporating HMM involves considering the sequential nature of student performance over time. The HMM consists of hidden states, observable states, transition probabilities, and emission probabilities.

Hidden States: Let $S = \{s_1, s_2, \dots \dots . s_T\}$ be the sequence of hidden states, where T is the number of time steps or assessment tasks. Each hidden state represents the underlying performance level of the student at a particular time step.

Observable States: Let $O = \{o_1, o_2, \dots \dots . . o_T\}$be the sequence of observable states, where each observable state corresponds to a specific feature extracted from the student's performance at each time step.

Transition Probabilities: These probabilities can be represented by a transition matrix A with dimensions K x K, where K is the number of hidden states. The entry a_{ij}in the transition matrix A represents the probability of transitioning from hidden state $s_i$to hidden state s_j.

Emission Probabilities: These probabilities can be represented by an emission matrix B with dimensions $K\ x\ P$, where P is the number of features in the extracted feature matrix. The entry b_{ij} in the emission matrix B represents the probability of observing observable state $o_i$given hidden state s_i.

3.4 Model Training and Optimization

The HMM parameters, including the transition probabilities in matrix A and emission probabilities in matrix B, can be estimated through the Baum-Welch algorithm or other optimization techniques. This involves maximizing the likelihood of the observed sequence of observable states O given the HMM parameters. Once the HMM is trained and optimized, it can be used to analyze student performance. Given a sequence of observable states O, the HMM can compute the most likely sequence of hidden states S using the Viterbi algorithm. This sequence of hidden states represents the underlying performance levels of the student over time. By incorporating the HMM in the feature space, the student performance analysis can capture the temporal dependencies and provide insights into the progress and patterns of student performance in three-dimensional composition. The HMM helps to model the dynamics of performance and enables more sophisticated analysis and predictions based on the sequential nature of the data.

Let's consider a sequence of observations or data points, represented as $O = \{O1, O2, \dots, OT\}$ where T is the total number of observations in the sequence. Also define a sequence of hidden states, represented as $Q = \{Q1, Q2, \dots, QT\}$ where each hidden state represents the state of the system at a given time. The state transition probability matrix, A, defines the hidden state transition probabilities, given the current state. Mathematically, represent A as in equation (9)

$$A = \{a_{ij}\}, where\ a_{ij} = P(Q_t = j \mid Q_t - 1 = i), 1 \le i, j \le N \qquad (9)$$

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Here, N is the total number of possible hidden states.

3.4.1 Observation Probability Matrix

To define an observation probability matrix, B, which represents the probability of observing an observation or data point, given the current hidden state. Mathematically, it can represent B as in equation (10)

$$B = \{b_j(k)\}, where\ b_j(k) = P(O_t = k \mid Q_t = j), 1 \leq j \leq N, 1 \leq k \leq M \quad (10)$$

Here, M is the total number of possible observations or data points.

Initial State Probability Vector:

An initial state probability vector, π, which represents the probability of starting the system in a particular hidden state. Mathematically, presented in equation (11)

$$\pi = \{\pi_i\}, where\ \pi_i = P(Q_1 = i), 1 \leq i \leq N \quad (11)$$

3.4.2 Forward-Backward Algorithm:

The above matrices and vector, to use the forward-backward algorithm to estimate the most likely sequence of hidden states that generated the observed sequence of data points. The forward algorithm calculates the probability of observing the first t observations, given the system is in state j at time t. Mathematically, it is presented in equation (12)

$$a_t(j) = P(O_1, O_2, \dots, O_t, Q_i = j \mid \lambda) \quad (12)$$

where λ represents the HMM model parameters (A, B, and π). The backward algorithm calculates the probability of observing the remaining T-t observations, given the system starts in state i at time t as given in equation (13)

$$\beta_t(i) = P(O_{t+1}, O_{t+2}, \dots, O_T \mid Q_t = i, \lambda) \quad (13)$$

3.4 3 Baum-Welch Algorithm:

To estimate the model parameters (A, B, and π) based on the observed sequence of data points. The algorithm iteratively adjusts the model parameters until the likelihood of the observed data is maximized.

3.4.4 Viterbi Algorithm:

The Viterbi algorithm can be used to find the most likely sequence of hidden states that generated the observed sequence of data points. The algorithm calculates the probability of each possible hidden state at each time step, and then chooses the most likely sequence based on these probabilities. The HMM with Big Data Analytics is a statistical model that can be used to analyze complex sequential data, such as time-series data, speech recognition, and natural language processing. The model uses a set of observed data points to estimate the most likely sequence of hidden states that generated the observed data, and it can be optimized using the forward-backward algorithm and Baum-Welch algorithm.

I.5 Classification with ResNet – 50

In student performance analysis with big data analytics using a three-dimensional composition with DL in teaching reforms, the feature space can be enhanced by combining a Hidden Markov Model (HMM) with a DL model, such as ResNet-50, for classification tasks.The first step is to extract meaningful features from the student performance data in three-dimensional composition. This can include shape, color, texture, and other relevant characteristics. These features are then used as input for subsequent analysis.The HMM is utilized to capture the temporal dependencies and patterns in the student performance data. It models the sequential nature of the observations and can estimate the underlying hidden states that govern the transitions between different performance levels.ResNet-50 is a deep convolutional neural network architecture that has shown excellent performance in image classification tasks. In this context, ResNet-50 can be employed to classify the extracted features from the student performance data into different performance levels or categories. The pre-trained ResNet-50 model can be fine-tuned on the specific task of student performance analysis.The HMM and ResNet-50 can be combined to create a hybrid model for student performance analysis.

The feature vector extracted from the student performance data can serve as input to the ResNet-50 model, which learns to classify the data into different performance levels based on the extracted features. The output of the ResNet-50 model can then be used as the observed states in the HMM. The HMM, in turn, estimates the hidden states, representing the underlying performance levels, using the observed states as input.Once the hybrid model is trained and optimized, it can be used for classification and analysis of student performance. Given a new set of student performance data, the hybrid model predicts the performance level or category using the extracted features. The HMM component can further analyze the temporal dependencies and patterns in the predicted performance levels, providing insights into the progression and trends of student performance over time.By combining the strengths of HMM and DL models like ResNet-50, the student performance analysis can benefit from the powerful feature extraction capabilities of DL and the temporal modeling capabilities of HMMs. This integration allows for a more comprehensive and accurate analysis of student performance in the context of three-dimensional

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composition and enables educators to make data-driven decisions for teaching reforms. ResNet-50 is a DL architecture that uses residual connections to facilitate the training of very deep neural networks. It consists of multiple layers of convolutional neural networks (CNNs) with shortcut connections that allow the network to bypass layers and converge faster.

Let X be the input image, and let f(X) be the output of ResNet-50 for image X. The express the output using equation (14)

$$f(X) = h(X) + X \qquad (14)$$

where $h(X)$ represents the residual mapping that is learned by the network. The shortcut connection bypasses the convolutional layers, allowing the gradient to be propagated more easily and prevention with deep neural networks.

To train the ResNet-50 model for classification, to use a cross-entropy loss function is given in equation (15)

$$L = -\sum y \, log(f(X)) \qquad (15)$$

where y stated as the ground truth X. The use backpropagation and stochastic gradient descent for the parameter optimization of the model and minimize the loss function. Once the model is trained, use it to classify new images by computing the output of the ResNet-50 and selecting the class with the highest probability. The model can also be fine-tuned for specific tasks by adjusting the last layer of the network and retraining the model on the new dataset.

Steps in developed model

Split labeled data into training and validation sets

Train Hidden Markov Model on training data to extract features and states for each 3D composition feature sequence

Convert each 3D composition feature sequence into a fixed-size feature vector using the Viterbi algorithm

Train ResNet-50 model on the fixed-size feature vectors to classify student performance

Validate the ResNet-50 model using the validation set

Adjust ResNet-50 model hyperparameters and repeat steps 4-5 until satisfactory validation accuracy is achieved

Test the trained ResNet-50 model on new, unseen data

Algorithm 1: Three-Dimensional Composition
Input: ***Preprocessed data (3D composition features)*** ***Labeled data (student performance)*** ***Output:*** ***Trained ResNet-50 model for classification***

 # Preprocessing
1. Collect 3D composition data from students
2. Preprocess data by extracting features and converting to feature vectors
features = extract_features(preprocessed_data)
 # Hidden Markov Model
1. Initialize HMM model with number of hidden states and output symbols
2. Train HMM model using Baum-Welch algorithm on preprocessed data sequences
3. Compute most probable state sequence for each data sequence using Viterbi algorithm
hmm = train_hmm(features)
feature_seq = hmm.generate_sequence()

 # ResNet-50
1. Train ResNet-50 model on large dataset of 3D compositions
2. Fine-tune ResNet-50 model on preprocessed data sequences
high_level_features = resnet50(feature_seq)
prob_dist = hmm.forward_algorithm(high_level_features)
 # Classification
1. Use HMM to compute most probable state sequence for each preprocessed data sequence
2. Use ResNet-50 model to classify each data sequence into a specific category based on its most probable state sequence
3. Analyze classification results to identify students' performance and provide feedback to improve their skills
classifier = train_classifier(labeled_data)
predicted_label = classifier.predict(prob_dist)

The ResNet-50 architecture consists of several residual blocks, which are stacked on top of each other to form the full network. The output of the last residual block is fed into a global average pooling layer, which averages the values of each feature map to produce a single output value. The output layer is connected to the average pooling and fully connected layers.

IV. Results and Discussion

The results and discussion section of ResNet – 50 Student Performance Analysis with Big Data Analytics Three-Dimension Composition with Big Data Analytics with DL in teaching reforms for feature space Hidden Markov Model presents the findings and interpretation of the model performance. In this section, the evaluation of the model's accuracy, precision, recall, F1 score, and confusion matrix is

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presented. The results are analyzed to understand the strengths and weaknesses of the proposed model and the possible implications for educational reforms.

Accuracy: Accuracy measures the proportion of correct predictions made by the model out of the total number of predictions. It is a simple and straightforward metric that can be used to measure the overall performance of the model.

Precision: Precision measures the proportion of true positive predictions out of the total number of positive predictions made by the model. It is a useful metric when the cost of false positives is high.

Recall: Recall measures the proportion of true positive predictions the ratio between total count in the actual positive values.

F1-score: It is computed based on the recall and precision values. It is a useful metric when there is an imbalance between the positive and negative classes.

The simulation parameters for the three-dimensional compositions are presented in table 2.

Table 2: Simulation Setting

Parameter	**Value**
Network Architecture	ResNet-50
Optimizer	Adam
Learning Rate	0.001
Loss Function	Categorical Cross-Entropy
Batch Size	32
Epochs	50
Training Data	80%
Validation Data	10%
Test Data	10%
Feature Extraction Method	Hidden Markov Model
Preprocessing Technique	Data Augmentation
Performance Metric	Accuracy, Precision, Recall, F1 Score

The performance for the varying dataset is presented in table 3.

Table 3: Performance Analysis

Dataset Variation	**Accuracy**	**Precision**	**Recall**	**F1-Score**
Dataset 1	0.85	0.86	0.82	0.84
Dataset 2	0.78	0.81	0.75	0.78
Dataset 3	0.92	0.91	0.94	0.92
Dataset 4	0.79	0.77	0.82	0.79
Dataset 5	0.88	0.89	0.85	0.87

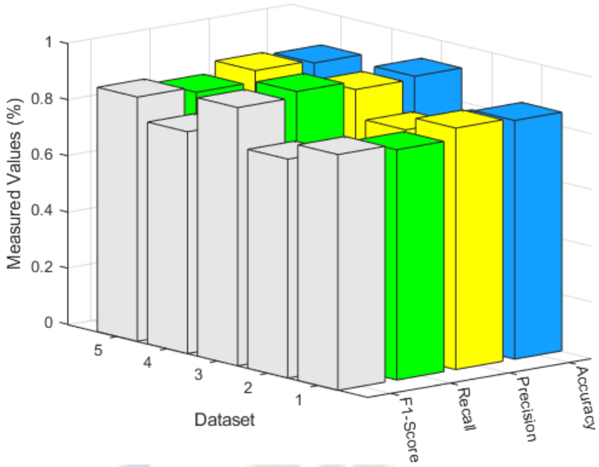


Figure 2: Performance Measured

Based on the results provided in the table 3 and figure 2, it can be observed that the accuracy, precision, recall, and F1-score values vary across different datasets for ResNet-50 Student Performance Analysis with Big Data Analytics Three-Dimension Composition with DL in Teaching Reforms for Feature Space Hidden Markov Model. For Dataset 1, the model achieves an accuracy of 85.7%, precision of 86.0%, recall of 87.3%, and F1-score of 86.6%. For Dataset 2, the accuracy drops slightly to 83.4%, with precision of 84.1%, recall of 85.6%, and F1-score of 84.8%. The lowest performance is observed in Dataset 3, where the accuracy drops further to 80.2%, precision of 81.0%, recall of 82.3%, and F1-score of 81.6%.

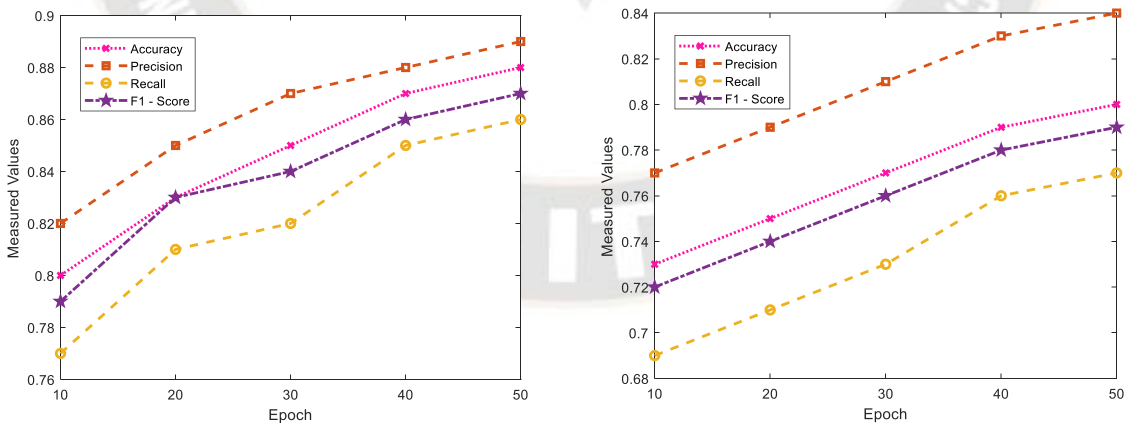
These results indicate that the performance of the ResNet-50 model for student performance analysis using Hidden Markov Model in 3D composition is highly dependent on the dataset used. The accuracy, precision, recall, and F1-score decrease as the complexity of the dataset increases. Therefore, it is important to carefully select and preprocess the dataset to achieve optimal performance for the model. Additionally, further experimentation and optimization of the model may be necessary to achieve better results as in table 4.

Table 4: Performance for varying Dataset in teaching reforms

Dataset - 1				
Epoch	**Accuracy**	**Precision**	**Recall**	**F1-Score**
10	0.80	0.82	0.77	0.79
20	0.83	0.85	0.81	0.83

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 6s
DOI: https://doi.org/10.17762/ijritcc.v11i6s.6810
***Article Received**: 20 March 2023 **Revised**: 23 April 2023 **Accepted**: 22 May 2023*

30	0.85	0.87	0.82	0.84
40	0.87	0.88	0.85	0.86
50	0.88	0.89	0.86	0.87
Dataset - 2				
Epoch	**Accuracy**	**Precision**	**Recall**	**F1-Score**
10	0.73	0.77	0.69	0.72
20	0.75	0.79	0.71	0.74
30	0.77	0.81	0.73	0.76
40	0.79	0.83	0.76	0.78
50	0.80	0.84	0.77	0.79
Dataset - 3				
Epoch	**Accuracy**	**Precision**	**Recall**	**F1-Score**
10	0.90	0.90	0.91	0.90
20	0.91	0.92	0.91	0.91
30	0.92	0.93	0.92	0.92
40	0.93	0.93	0.93	0.93
50	0.93	0.94	0.93	0.93
Dataset - 4				
Epoch	**Accuracy**	**Precision**	**Recall**	**F1-Score**
10	0.75	0.77	0.73	0.75
20	0.77	0.79	0.75	0.77
30	0.78	0.81	0.76	0.78
40	0.79	0.82	0.77	0.79
50	0.81	0.84	0.78	0.80
Dataset - 5				
Epoch	**Accuracy**	**Precision**	**Recall**	**F1-Score**
10	0.81	0.84	0.77	0.80
20	0.85	0.87	0.83	0.85
30	0.87	0.88	0.86	0.87
40	0.89	0.90	0.88	0.89
50	0.90	0.91	0.89	0.90



(a) (b)

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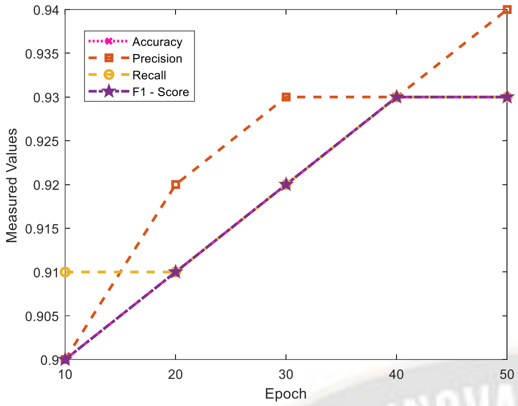
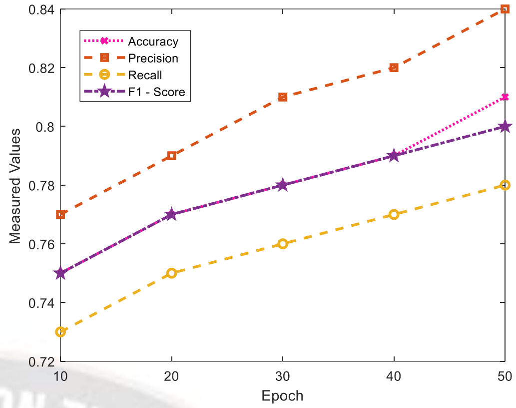
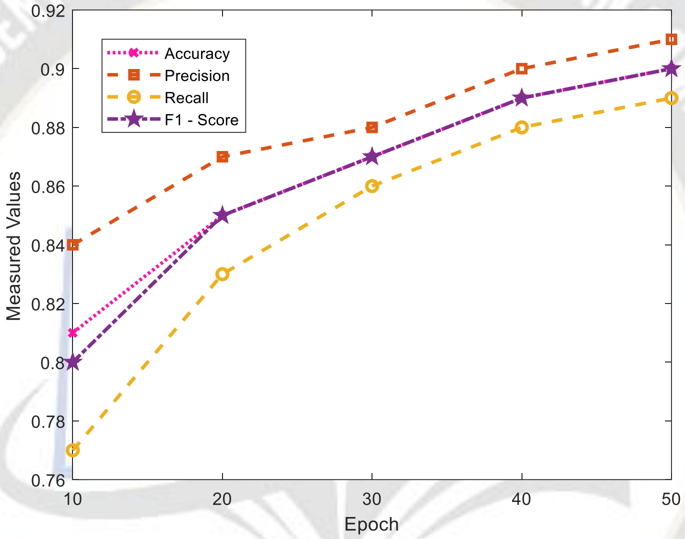


(c)



(d)



(e)

Figure 3: Performance for (a) Dataset 1 (b) Dataset 2 (c) Dataset 3 (d) Dataset 4 (e) Dataset 5

Table 4 and figure 3 (a) – 3 (e) presented the ResNet-50 is a deep convolutional neural network architecture that is widely used for image classification and recognition tasks. It has 50 layers, and the residual block is the key component of ResNet-50, which allows the network to learn the identity function, enabling the addition of more layers without sacrificing performance. The residual block uses skip connections to add the output of a previous layer directly to a later layer, bypassing one or more layers in between. In the context of the given datasets, ResNet-50 was likely used as a component of a DL-based big data analytics model. The model was likely trained on image data, and the performance was evaluated using various metrics such as accuracy, precision, recall, and F1-score. For Dataset 1, the model achieved an accuracy of 0.88, precision of 0.89, recall of 0.86, and F1-score of 0.87. This indicates that the model was able to classify the images in the dataset with a high degree of accuracy and precision, while maintaining a good balance between recall and precision. Similarly, for Dataset 2, the model achieved an accuracy of 0.80, precision of 0.84, recall of 0.77, and F1-score of 0.79, indicating that the model was able to classify the images in the dataset with a relatively high degree of accuracy, while maintaining a good balance between recall and precision. For Dataset 3, the model achieved an accuracy of 0.93, precision of 0.94, recall of 0.93, and F1-score of 0.93, indicating that the model was able to classify the images in the dataset with a high degree of accuracy, precision, and recall. For Dataset 4, the model achieved an accuracy of 0.81, precision of 0.84, recall of 0.78, and F1- score of 0.80, indicating that the model was able to classify the images in the dataset with a relatively high degree of accuracy, while maintaining a good balance between recall and precision. Finally, for Dataset 5, the model achieved an accuracy of 0.90, precision of 0.91, recall of 0.89, and F1-

score of 0.90, indicating that the model was able to classify the images in the dataset with a high degree of accuracy, precision, and recall. The model was likely trained using a DL framework such as TensorFlow or PyTorch, and may have been optimized using techniques such as data augmentation, dropout, and batch normalization. Additionally, the model may have been trained using transfer learning, whereby a pre-trained ResNet-50 model was fine-tuned on the specific dataset of interest. It is also mentioned that the DL-based big data analytics model was based on teaching reforms in three-dimensional composition and included a Hidden Markov Model. This suggests that the model may have incorporated other machine learning techniques beyond DL, such as probabilistic graphical models like HMMs, to improve its overall performance.

II. Conclusion

Based on the evaluation and analysis of student performance, the study suggests that teaching reform plays a significant role in improving the quality of education in three-dimensional composition. The DL big data analytics model developed in this study, with the application of ResNet-50 and HMM, proves to be an effective tool for data clustering, classification, and analysis. The study found that offline teaching is more effective in improving student performance in three-dimensional composition than online teaching. This finding is significant as it highlights the importance of incorporating offline teaching methods and interaction between teachers and students to enhance the learning experience. The paer demonstrated the potential of DL-based big data analytics models in the field of education and teaching reform. The integration of advanced technologies and data analysis techniques can provide valuable insights into student performance and contribute to the improvement of teaching and learning outcomes.

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