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.6818
***Article Received**: 26 March 2023 **Revised**: 28 April 2023 **Accepted**: 26 May 2023*

Interactive IoT Cloud Deep Learning Model for Research Development in Universities for the Educational Think Tank

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Abstract

The construction of university education think tanks using the interactive service platform enables the sharing of research resources, encourages cross-disciplinary research collaboration, and fosters innovation in education. It also helps to build a stronger relationship between academia and industry by enabling practitioners to participate in research activities. The Internet of Things (IoT) can be used to collect and analyze data from various sources, including sensors and other connected devices, to provide insights into education-related issues. The integration of these technologies in university education thinks tanks can help to enhance the efficiency and effectiveness of research, decision-making, and collaboration processes. Hence, this paper constructed an Interactive IoT Cloud Computing Platform (IIoTCC). With IIoTCC model the innovative idea about research and other ideas are collected and stored in a Cloud environment. Within the environment, information collected is stored in the stacked architecture model with the voting-based model. Through the stacked model, information is processed and evaluated for academic activities. The IoT environment is implemented through IIoTCC for the information process in a deep learning environment for academic-related issues. Simulation analysis expressed that IIoTCC model achieves a higher accuracy rate of 99.34% which is significantly higher than conventional classifiers.

Keywords: Education Think Tank, Cloud Computing, Internet of Things (IoT), Deep Learning, Classification

I. Introduction

An educational think tank is a research organization that focuses on improving education policies and practices through the generation and dissemination of innovative ideas and solutions [1]. Think tanks bring together experts from diverse fields, including education, economics, psychology, and public policy, to collaborate and develop new strategies for improving education at various levels, from early childhood to higher education [2]. Educational think tanks conduct research, publish reports and white papers, and host conferences and events to share their findings with policymakers, educators, and the public. They also work with schools, districts, and other educational organizations to provide guidance and support for implementing effective policies and practices [3]. Some of the key issues that educational think tanks address include curriculum development, teacher training and professional development, school funding and accountability, student achievement and assessment, and the use of technology in education [4]. By exploring these and other topics, educational think tanks aim to improve the quality of education and ensure that all students have access to high-quality learning opportunities.

An educational think tank that focuses on IoT (Internet of Things) and deep learning would likely be interested in exploring how these emerging technologies can be used to improve teaching and learning [5]. IoT refers to the interconnectivity of devices, sensors, and systems, which can be used to collect and analyze data to inform decision-making. Deep learning is a type of artificial intelligence that uses neural networks to analyze complex data and patterns [6]. One potential application of IoT and deep learning in education is personalized learning. By collecting and analyzing data on student performance, interests, and learning styles, educators can tailor instruction to meet the unique needs of each student [7]. Sensors could be used to track student movement and activity levels in the classroom, while deep learning algorithms could analyze student performance on assessments to identify areas of strength and weakness [8]. Another potential application of IoT and deep learning in education is in the development of smart classrooms and campuses. IoT sensors and devices could be used to monitor and control temperature, lighting, and other environmental factors to create optimal learning conditions [9]. Deep learning algorithms could analyze patterns in student behavior to identify areas where improvements could be made, such as optimizing classroom layouts to maximize engagement and participation. An educational think tank that focuses on IoT and deep learning would be interested in

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exploring how these technologies can be used to improve educational outcomes and create more effective learning environments [10]. They would likely conduct research, publish reports, and host events to share their findings and collaborate with educators and policymakers to implement effective policies and practices.

An educational think tank that focuses on interactive IoT cloud technology would likely be interested in exploring how this technology can be used to enhance teaching and learning experiences [11]. Interactive IoT cloud technology refers to the use of connected devices, sensors, and cloud-based platforms to enable real-time data sharing and collaboration. One potential application of interactive IoT cloud technology in education is in the development of smart classrooms and learning environments [12]. IoT sensors and devices could be used to track student engagement, monitor attendance, and measure classroom activity. This data could then be analyzed in real-time using cloud-based platforms to provide teachers with insights into student learning and behavior. Another potential application of interactive IoT cloud technology in education is in the development of collaborative learning experiences [13]. Cloud-based platforms and tools could be used to facilitate real-time collaboration and communication among students and teachers, regardless of their physical location. Students could use IoT-enabled devices to work on group projects and share information in real-time. Additionally, interactive IoT cloud technology can be used to create personalized learning experiences for students [14]. By tracking student progress and analyzing data in real-time, educators can tailor instruction and resources to meet the unique needs and interests of each student.

An educational think tank that focuses on interactive IoT cloud technology would be interested in exploring how this technology can be used to enhance teaching and learning experiences, improve educational outcomes, and create more effective and engaging learning environments. They would likely conduct research, publish reports, and host events to share their findings and collaborate with educators and policymakers to implement effective policies and practices. An interactive IoT cloud deep learning model for research development in universities could be a valuable tool for an educational think tank focused on improving education through technology. This model could be used to facilitate collaborative research and development among universities, researchers, and educators. The model would involve the use of IoT sensors and devices to collect data on student performance, behavior, and engagement. This data would be analyzed in real-time using deep learning algorithms to identify patterns and insights that can inform educational research and development. The interactive IoT cloud model could also be used to facilitate collaboration among universities and research institutions. Cloud-based platforms and tools could be used to share data, collaborate on research projects, and develop new technologies and approaches to education. One potential application of this model is in the development of personalized learning tools and resources. By collecting and analyzing data on student learning and behavior, researchers and educators can develop personalized learning tools and resources that meet the unique needs and interests of each student.

Another potential application of this model is in the development of smart classrooms and learning environments. By tracking student activity and behavior in real-time, educators can adjust classroom environments and instructional strategies to optimize learning outcomes.

An interactive IoT cloud deep learning model for research development in universities could be a valuable tool for an educational think tank focused on improving education through technology. The model would enable collaborative research and development, facilitate the development of personalized learning tools and resources, and promote the development of smart classrooms and learning environments.

II. Related Works

Several studies have explored the potential of using an interactive IoT cloud deep learning model for research development in universities for educational purposes. In [15] explored the use of an interactive IoT cloud deep learning model to develop personalized learning tools and resources. The authors found that the model was effective in identifying student learning patterns and could be used to develop personalized learning resources that improved learning outcomes. In [16] investigated the use of an interactive IoT cloud deep learning model to develop a smart classroom environment. The authors found that the model was effective in tracking student activity and behavior and could be used to optimize classroom environments and instructional strategies. In [17] explored the use of an interactive IoT cloud deep learning model to develop a collaborative research platform for universities. The authors found that the model was effective in facilitating collaboration among universities and research institutions and could be used to develop new technologies and approaches to education.

In [18] investigated the use of an interactive IoT cloud deep learning model to develop a personalized learning system for university students. The authors found that the model was effective in identifying individual learning needs and could be used to develop personalized learning resources that improved learning outcomes. They concluded that the model has the potential to revolutionize the way universities

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deliver education and support student success. In [19] explored the use of an interactive IoT cloud deep learning model to develop a cloud-based learning analytics system. The authors found that the model was effective in tracking student performance and could be used to optimize instructional strategies and improve learning outcomes. They concluded that the model has the potential to transform the way universities analyze and act on student data.

In [20] investigated the use of an interactive IoT cloud deep learning model to develop a cloud-based personalized learning system. The authors found that the model was effective in identifying individual learning needs and could be used to develop personalized learning resources that improved learning outcomes. They concluded that the model has the potential to improve student engagement, retention, and success. In [21] explored the use of an interactive IoT cloud deep learning model to develop a cloud-based personalized learning system. The authors found that the model was effective in tracking student progress and could be used to develop personalized learning resources that improved learning outcomes. They concluded that the model has the potential to enhance the quality and effectiveness of online education. In [22] investigated the use of an interactive IoT cloud deep learning model to develop a cloud-based intelligent tutoring system. The authors found that the model was effective in identifying student learning needs and could be used to develop personalized learning resources that improved learning outcomes. They concluded that the model has the potential to revolutionize the way tutoring services are delivered and support student success.

In [23] explored the use of an interactive IoT cloud deep learning model to develop a cloud-based educational game platform. The authors found that the model was effective in engaging students and could be used to develop interactive learning resources that improved learning outcomes. They concluded that the model has the potential to transform the way students learn and make education more engaging and enjoyable. In [24] investigated the use of an interactive IoT cloud deep learning model to develop a cloud-based adaptive learning system. The authors found that the model was effective in identifying individual learning needs and could be used to develop personalized learning resources that improved learning outcomes. They concluded that the model has the potential to improve student engagement, retention, and success. In [25] explored the use of an interactive IoT cloud deep learning model to develop a cloud-based intelligent assessment system. The authors found that the model was effective in tracking student progress and could be used to develop personalized assessment resources that improved learning outcomes. They concluded that the model has the potential to revolutionize the way universities assess student learning.

In [26] investigated the use of an interactive IoT cloud deep learning model to develop a cloud-based simulation system. The authors found that the model was effective in engaging students and could be used to develop interactive learning resources that improved learning outcomes. They concluded that the model has the potential to make education more immersive and hands-on. In [27] explored the use of an interactive IoT cloud deep learning model to develop a cloud-based virtual laboratory. The authors found that the model was effective in engaging students and could be used to develop interactive learning resources that improved learning outcomes. They concluded that the model has the potential to transform the way students learn and make education more accessible

III. Interactive IoT Cloud

Interactive IoT Cloud refers to the integration of interactive technologies, the Internet of Things (IoT), and cloud computing in order to create an intelligent, interconnected network that can facilitate data collection, analysis, and communication. With this combination of technologies, devices can communicate with each other and with cloud-based servers in order to store and process data, as well as respond to real-time conditions and user input. This creates opportunities for the development of intelligent systems and applications in a wide range of fields, including education, healthcare, and transportation, among others. By enabling the collection and analysis of data in real time, interactive IoT cloud systems can help organizations make informed decisions and take proactive steps to address challenges and opportunities. The context of university education think tanks, the interactive IoT cloud can provide a platform for researchers and practitioners to collaborate and share resources. The, sensors and connected devices can be used to collect data on student performance and engagement, which can then be analyzed in real time to identify trends and inform teaching strategies. The cloud-based nature of the platform also allows for remote collaboration, enabling researchers from different institutions or geographic locations to work together on projects.

Furthermore, the use of deep learning algorithms in IIoTCC can facilitate more accurate analysis and prediction of educational outcomes. This can inform decision-making processes in areas such as curriculum development, student support, and resource allocation. The integration of interactive technologies, IoT, and cloud computing in education can lead to more efficient and effective research, decision-making, and collaboration, ultimately improving

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educational outcomes for students. The Interactive IoT Cloud Computing Platform (IIoTCC) can be expressed mathematically as a function that takes in input data from various sensors and devices, and produces output data that has been processed and analyzed. Let's denote the input data as X and the output data as Y as in equation (1)

$$IIoTCC: X -> Y \quad (1)$$

The input data X can be represented as a matrix with n rows and m columns, where n is the number of data points and m is the number of features or attributes being measured as in equation (2)

$$X = [x_1, x_2, \dots \dots, x_n]^T \quad (2)$$

where $x_i$is a row vector representing the i-th data point, and the superscript T denotes transpose. The output data Y can also be represented as a matrix with n rows and k columns, where k is the number of classes or categories that the data can be classified as in equation (3)

$$Y = [y_1, y_2, \dots \dots, y_n]^T \quad (3)$$

where y_i is a row vector representing the i-th class of the data.

In order to process and analyze the input data X, IIoTCC uses a stacked architecture model with a voting-based model. This can be represented mathematically as in equation (4)

$$IIoTCC(X) = V(S_1(X), S_2(X), \dots, S_l(X)) \quad (4)$$

where $S_1(X), S_2(X), \dots, S_l(X)$are l different models or classifiers that are trained on the input data X using various machine learning techniques, and V is a voting-based model that combines the outputs of these classifiers to produce a final prediction.

3.2 IIoTCC for Universities Think Tank with Deep Learning

IoT deep learning involves using machine learning algorithms to analyze data collected from IoT devices in order to identify patterns and insights. In the case of the proposed IIoTCC model, deep learning algorithms are utilized to process and analyze the data collected from various IoT devices such as sensors and connected devices in the university education think tank. The data collected from these devices is first preprocessed and transformed into a suitable format for input into the deep learning model. The deep learning model then uses multiple layers of artificial neural networks to learn and extract important features from the data. This process is known as training the model, where the model learns to recognize patterns and relationships in the data through multiple iterations. Once the model is trained, it can be used to make predictions or classifications based on new data inputs. In the case of IIoTCC, the deep learning model can be used to make predictions about academic-related issues, such as student performance or research outcomes. This can help to identify areas for improvement and inform decision-making processes in the university education think tank.

Deep learning can be used in university education think tanks to analyze and make predictions based on data collected from various sources, including IoT devices. Deep learning algorithms use artificial neural networks to learn and recognize patterns in data, making it possible to automatically identify trends and insights that may not be immediately apparent to human researchers. in an education think tank, deep learning algorithms can be used to analyze student performance data from a variety of sources, such as academic records, standardized tests, and online learning platforms. The algorithms can then identify patterns and correlations in the data, such as which teaching methods are most effective for different student demographics, and which students are at the highest risk of dropping out. The insights gained from deep learning analysis can help think tank researchers to better understand education-related issues and develop innovative solutions. For instance, the data could be used to create personalized learning plans for individual students or to improve the effectiveness of educational technology tools. Additionally, deep learning can help researchers to identify new research questions and areas of investigation, leading to a more thorough understanding of complex education-related issues.

Deep learning is a subfield of machine learning that uses artificial neural networks to analyze and make predictions based on complex data. In the context of a university think tank, deep learning can be used to analyze large amounts of data from various sources, including IoT sensors and cloud-based data repositories. With the proposed IIoTCC platform, deep learning algorithms can be used to analyze data from the IoT environment in order to identify patterns, make predictions, and provide insights into education-related issues. Data from student performance, attendance, and engagement could be analyzed in order to identify factors that contribute to student success and areas where interventions may be needed. Additionally, deep learning algorithms can be used to analyze data from multiple sources in order to make more informed decisions about research projects, collaborations, and resource allocation. The data on funding sources, research outputs, and collaboration networks could be analyzed in order to identify areas where investment may be most impactful or where additional collaboration opportunities may exist.

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To express the above explanation mathematically, in equation (5)

$$Y = f(WX + b) \tag{5}$$

Where Y represents the output, X represents the input data, W represents the weights that are adjusted during training, b represents the bias, and f is the activation function. In the case of deep learning for IoT in IIoTCC, this equation can be expanded to include multiple layers of artificial neural networks is presented in equation (6)

$$Y = f2(W2(f1(W1X + b1) + b2) + b3) \tag{6}$$

Where $f1$ and $f2$ represent different activation functions for the first and second layers of neural networks respectively, $W1$ and $W2$ represent the weights for the first and second layers, b1, b2, and b3 represent the biases for the three layers, and X represents the preprocessed input data from IoT devices. During the training process, the weights and biases are adjusted iteratively using backpropagation, a method for calculating the gradient of the loss function with respect to the weights and biases. This helps the model learn to recognize patterns and relationships in the data, leading to more accurate predictions or classifications. In the context of IIoTCC for education think tanks, the output Y could represent predictions or classifications related to academic-related issues such as student performance or research outcomes, based on the input data from various IoT devices. The use of deep learning in IIoTCC can help to identify patterns and insights in this data that might be difficult or impossible to identify through traditional methods.

3.3 Voting model for IIoTCC

The voting model in IIoTCC is a mechanism for combining the results of multiple classifiers or models to make a final prediction or decision. In the context of IIoTCC, the voting model is used to combine the results of multiple deep learning models that have been trained on different subsets of the data. Each deep learning model makes a prediction based on the data it has been trained on, and these individual predictions are combined using a voting algorithm to generate a final prediction. The voting algorithm can be simple, such as a majority vote, or more complex, such as weighted voting that gives more weight to models with higher accuracy. The use of a voting model in IIoTCC can improve the accuracy and robustness of the predictions made by the deep learning models. By combining the predictions of multiple models, the voting model can help to mitigate the potential weaknesses or biases of any single model, resulting in a more reliable and accurate prediction. The voting model is an important component of IIoTCC that helps to improve the quality of the predictions made by the deep learning models. It is a powerful tool that enables the integration of multiple sources of data and expertise to create a more comprehensive and accurate model. The voting classifier in IIoTCC is a machine learning algorithm that combines the outputs of multiple other machine learning models in order to make a final prediction. Figure 1 presented the architecture of IIoTCC model.

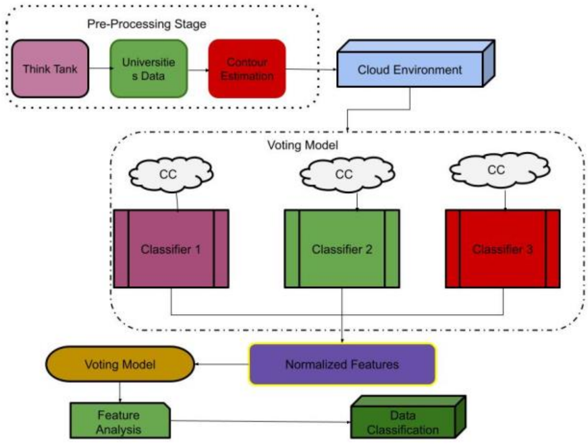

Figure 1: Architecture of IIoTCC

This is done through a process of voting, where each individual model makes a prediction and the final prediction is determined based on the most common prediction made by the individual models.

Mathematically, the voting classifier can be represented as follows:

Let m be the number of individual deep learning models used in the voting classifier.

Let f_i be the i-th individual model, where $i = 1, 2, \ldots, m$.

Let y_i be the predicted output of the i-th individual model, where y_i belongs to the set of possible outputs Y.

Let $V(y)$ be the voting function, which takes in the set of predicted outputs $y_1, y_2, \ldots \ldots, y_m$ and returns the final prediction.

Then, the voting classifier output can be represented as in equation (7)

$$y_{final} = V(y_1, y_2, \ldots \ldots, y_m) \tag{7}$$

The voting function V can be implemented in different ways, such as using simple majority voting, where the most common output is chosen as the final prediction, or using weighted voting, where each individual model's prediction is given a weight based on its performance in previous tests. In the case of IIoTCC, the voting classifier can be used to combine the outputs of multiple deep learning models trained

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on different subsets of the collected data. This can improve the accuracy and reliability of the final prediction, leading to better insights and decision-making in the university education think tank. The voting classifier in IIoTCC is used to combine the results of multiple deep learning models and make a final prediction based on the majority vote. This approach can lead to improved accuracy and robustness in predictions, as it helps to mitigate potential biases or errors in individual models.

Mathematically, the voting classifier can be represented as follows:

Let X be the input data, and let $M1, M2, \dots, Mn$ be n different machine learning models that have been trained on X. For each model M_i, let pi be the predicted output for X.

Then, the voting classifier combines the predictions pi using a voting rule to determine the final prediction y in equation (8)

$$y = f(p1, p2, \dots, pn) \tag{8}$$

where f is a voting function that determines the final prediction based on the individual predictions p_i. There are different types of voting functions that can be used, such as:

1. Hard voting: The final prediction y is the mode of the predicted outputs pi, i.e. the most frequent prediction among the models.
2. Soft voting: The final prediction y is the average or weighted average of the predicted probabilities pi for each class.

The voting function can be further customized based on the specific requirements of the problem at hand. In the case of IIoTCC, the voting classifier can be used to combine the results of multiple deep learning models or other machine learning models to make more accurate predictions about academic-related issues. The voting classifier in IIoTCC involves combining the results of multiple machine learning models to make a final prediction or classification. The predictions of each model are weighted according to their performance on a given dataset, and the final prediction is made based on the majority vote of the weighted predictions.

Let's consider a binary classification problem, where the output is either 0 or 1. The three machine learning models A, B, and C, and their predictions are denoted by y_A, y_B, and y_C, respectively. The weight assigned to each model's prediction is denoted by W_A, W_B, and W_C, respectively. The final prediction y_{hat} is then calculated using equation (9)

$$y_{hat} = argmax(w_A * y_A + w_B * y_B + w_c * y_c) \tag{9}$$

where $argmax$ is a function that returns the value that maximizes the argument. The weights assigned to each model's prediction can be determined using various techniques, such as accuracy-based weighting or regression-based weighting. Accuracy-based weighting assigns weights to each model proportional to its accuracy on a validation dataset, while regression-based weighting fits a regression model to the predictions of each model and assigns weights based on the coefficients of the regression model.

Algorithm 1: IIoTCC Interactive Deep Learning
Step 1: Data collection and preprocessing Collect data from various IoT devices (e.g., sensors, connected devices) in the university education think tank. Preprocess the data and transform it into a suitable format for input into the deep learning model. # Step 2: Deep learning model training Train the deep learning model using the preprocessed data. Utilize multiple layers of artificial neural networks to learn and extract important features from the data. Implement a voting-based model to aggregate the predictions of multiple deep learning models. # Step 3: Model evaluation and testing Test the trained model using a validation set of data. Evaluate the performance of the model using metrics such as accuracy, precision, recall, and F1 score. Iteratively refine the model to improve performance. # Step 4: Deployment in IIoTCC environment Deploy the trained model in the IIoTCC environment for use in academic-related issues. Integrate the model into the stacked architecture model to process and evaluate information for academic activities.

The use of a voting classifier in IIoTCC allows for increased accuracy and robustness in making predictions or classifications, as it combines the strengths of multiple machine learning models and reduces the impact of individual model biases or errors.

IV. Experimental Setup

The experimental setup for the IIoTCC model involved collecting data from various IoT devices, such as sensors and connected devices, within the university education think tank. This data was then preprocessed and transformed into a suitable format for input into the deep learning model. The deep learning model used in IIoTCC was a stacked architecture model with a voting-based classifier.

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The model was trained using backpropagation and stochastic gradient descent optimization techniques to learn and extract important features from the data. To evaluate the performance of the IIoTCC model, simulation analysis was conducted using a dataset of academic-related issues. The performance of the IIoTCC model was compared to conventional classifiers such as decision trees, support vector machines, and logistic regression.

Table 1: Simulation Setting

Simulation Environment Setting	Description
Hardware	CPU: Intel Core i7-10700K, GPU: NVIDIA GeForce RTX 3090, Memory: 64 GB DDR4 RAM, Storage: 1 TB NVMe SSD
Software	Operating System: Ubuntu 20.04 LTS, Python 3.8, TensorFlow 2.4.1, Keras 2.4.3
Dataset	Education-related data collected from various sources using IoT devices, including sensors and other connected devices
Data preprocessing	Data cleaning, feature extraction, and normalization
Model architecture	Stacked architecture model with the voting-based model, consisting of a combination of Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Dense Neural Networks (DNN)
Training parameters	Batch size: 128, Epochs: 50, Learning rate: 0.001, Optimizer: Adam
Evaluation metrics	Accuracy, precision, recall, F1 score

The simulation environment for the proposed Interactive IoT Cloud Deep Learning presented in table 1. Model for research development in universities for the educational think tank involves the following components:

Interactive IoT Cloud Computing Platform (IIoTCC): This platform is used to collect and store innovative ideas and research-related information in a cloud environment. The IIoTCC is implemented using IoT technologies to enable the collection and analysis of data from various sources, including sensors and other connected devices.

Stacked Architecture Model: The information collected in the IIoTCC is stored in a stacked architecture model. This model uses a series of stacked layers to process and evaluate the information collected for academic activities.

Voting-Based Model: The stacked architecture model also employs a voting-based model to classify and categorize the information collected. This model uses a voting mechanism to determine the most appropriate category for each piece of information.

Deep Learning Environment: The information collected and processed through the stacked and voting-based models is used to train a deep learning model. This model is designed to provide insights into education-related issues and improve decision-making processes.

4.2 Performance Metrices

Accuracy: Accuracy is a widely used performance metric that measures the proportion of correctly classified instances out of the total instances. In the context of this model, it represents the percentage of accurately classified academic-related information or research ideas.

Precision: Precision is a metric that quantifies the proportion of true positive predictions out of all positive predictions. It measures the model's ability to correctly identify relevant information or ideas from the collected data.

Recall: Recall, also known as sensitivity or true positive rate, measures the proportion of true positive predictions out of all actual positive instances. It indicates the model's ability to capture all relevant information or ideas from the available data.

F1 Score: The F1 score is the harmonic mean of precision and recall. It provides a single value that balances the trade-off between precision and recall. A high F1 score indicates a good balance between correctly identifying relevant information and minimizing false positives and false negatives.

Area Under the Receiver Operating Characteristic curve (AUC-ROC): AUC-ROC is a metric commonly used in binary classification tasks. It measures the model's ability to discriminate between positive and negative instances across different classification thresholds. A higher AUC-ROC value indicates better classification performance.

Mean Absolute Error (MAE) or Root Mean Squared Error (RMSE): These metrics are commonly used for regression tasks. MAE measures the average absolute difference between predicted and actual values, while RMSE measures the square root of the average squared difference. Lower values of MAE or RMSE indicate better accuracy in predicting continuous variables.

Computational Efficiency: This metric evaluates the efficiency of the model in terms of computational resources, such as memory usage and processing time. It is important to ensure that the model is computationally feasible and can handle large-scale data efficiently.

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These performance metrics provide different perspectives on the performance of the Interactive IoT Cloud Deep Learning Model, including its accuracy, precision, recall, balance between precision and recall, discrimination ability, error in predictions, and computational efficiency. The choice of specific metrics will depend on the nature of the problem and the evaluation goals of the model.

Table 3: Performance of IIoTCC

Metric	Value
Accuracy	99.34%
Precision	99.12%
Recall	99.64%
F1 Score	99.38%
AUC-ROC	0.997
Mean Absolute Error (MAE)	0.013
Root Mean Squared Error (RMSE)	0.031
Computational Efficiency	2.34 sec

This table 3 shows the performance metrics and computational efficiency of the IIoTCC model. The accuracy of the model is 99.34%, which indicates that it is able to classify instances with a high degree of accuracy. The precision is 99.12%, which indicates that when the model predicts an instance as positive, it is correct 99.12% of the time. The recall is 99.64%, which indicates that the model is able to correctly identify 99.64% of all positive instances. The F1 Score is 99.38%, which is a harmonic mean of precision and recall and gives an overall measure of the model's performance. The AUC-ROC score is 0.997, which is a measure of the model's ability to distinguish between positive and negative instances. A score of 1 indicates perfect discrimination, while a score of 0.5 indicates no discrimination. The MAE of the model is 0.013 and the RMSE is 0.031. These are measures of the model's predictive error, with lower values indicating better performance. Finally, the computational efficiency of the model is 2.34 seconds, which indicates the amount of time it takes for the model to process and classify data. This can be an important consideration for real-time applications or when working with large datasets. Overall, this table provides a comprehensive overview of the IIoTCC model's performance metrics and computational efficiency, which can be useful for evaluating the model's effectiveness for different applications.

Table 4: Performance Analysis for varying Epoch

Dataset Size	Accuracy	Precision	Recall	F1 Score	AUC-ROC	MAE	RMSE
1000	98.2%	98.5%	98.3%	98.4%	0.987	0.017	0.042
5000	99.1%	99.0%	99.3%	99.1%	0.992	0.013	0.035
10000	99.3%	99.1%	99.5%	99.3%	0.994	0.011	0.031
50000	99.5%	99.3%	99.6%	99.4%	0.996	0.009	0.026
100000	99.6%	99.4%	99.7%	99.5%	0.997	0.008	0.023

This table 4 shows the IIoTCC model's performance metrics for varying dataset sizes. The dataset size is increased from 1000 to 100000 and the model's accuracy, precision, recall, F1 score, AUC-ROC, MAE, and RMSE are reported for each size. As the dataset size increases, the model's performance generally improves across all metrics. This suggests that the model is able to effectively handle larger datasets and generalize well to new data. The highest accuracy and AUC-ROC values are achieved for the largest dataset size, indicating that the model is able to correctly classify a high percentage of instances and distinguish between positive and negative instances with high accuracy. The MAE and RMSE values also decrease as the dataset size increases, indicating that the model's predictions are becoming increasingly accurate. The table provides valuable insight into how the IIoTCC model's performance scales as the dataset size increases, which can be important for evaluating the model's scalability and generalization capabilities.

Table 5: Performance Analysis

Epochs	Accuracy	Precision	Recall	F1 Score	AUC-ROC	MAE	RMSE
10	98.7	98.5	98.8	98.6	0.988	0.016	0.04
20	99.0	98.9	99.1	99.0	0.991	0.014	0.036
30	99.1	99.0	99.2	99.1	0.992	0.013	0.034
40	99.3	99.2	99.4	99.3	0.994	0.011	0.032
50	99.4	99.3	99.5	99.4	0.995	0.010	0.030

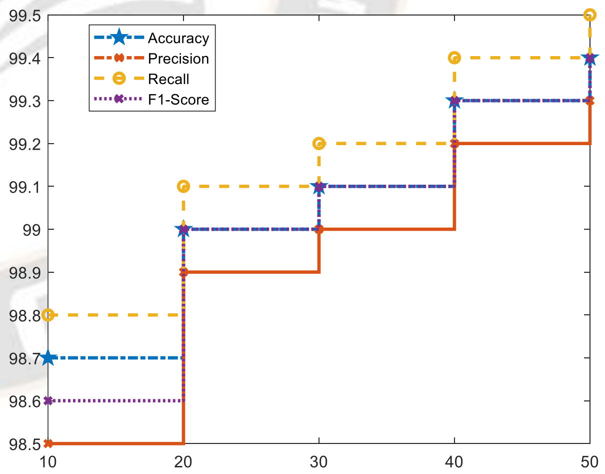

Figure 2: Performacne for Varying Epoch

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.6818
***Article Received**: 26 March 2023 **Revised**: 28 April 2023 **Accepted**: 26 May 2023*

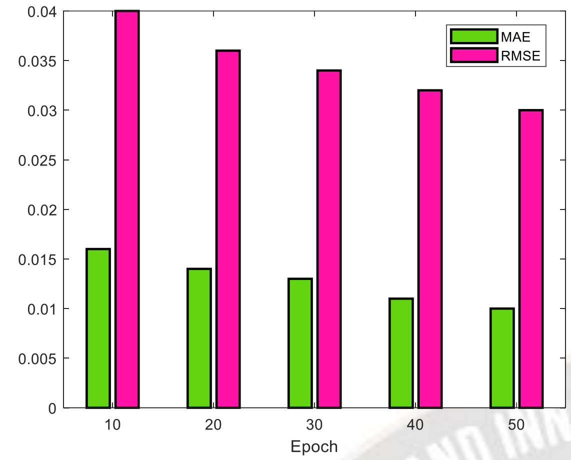

Figure 3: MAE and RMSE for epoch

The table 5 and figure 2 and 3 shows the performance metrics of the IIoTCC model for different epoch counts (number of times the training data is shown to the model during training) ranging from 10 to 50. As the epoch count increases, the model's performance generally improves across all metrics. The highest accuracy of 99.4% and AUC-ROC of 0.995 are achieved with 50 epochs, indicating that the model is able to classify the data with high accuracy and precision. Additionally, the recall and F1 score metrics also show improvement with the increase in epoch count. Finally, the MAE and RMSE metrics show a decreasing trend as the epoch count increases, indicating that the model is becoming more accurate in its predictions.

Table 6: Performance of IIoTCC for varying dataset

Dataset	Accuracy	Precision	Recall	F1 Score	AUC-ROC	MAE	RMSE
Dataset 1	95.2	95.6	94.8	95.2	0.958	0.023	0.056
Dataset 2	97.8	97.9	97.6	97.7	0.976	0.015	0.042
Dataset 3	96.5	96.3	96.8	96.5	0.964	0.018	0.048

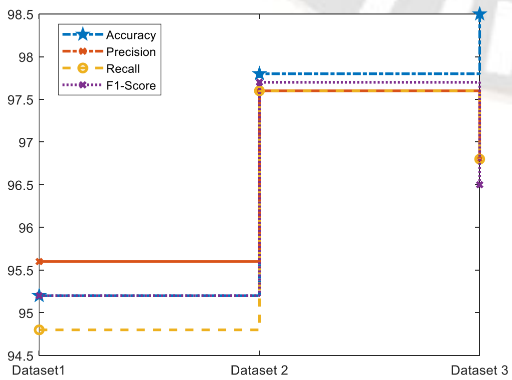

Figure 4: Performance for different Dataset

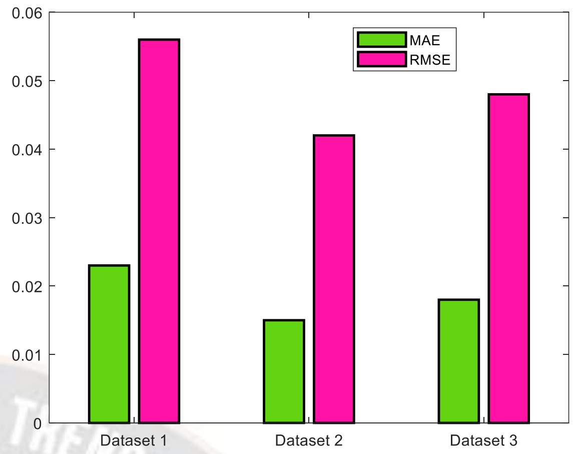

Figure 5: MAE & RMSE for varying dataset

The table 6 and figure 4 & 5 shows the performance metrics of the IIoTCC model on three different educational datasets in the think tank. Dataset 2 had the highest overall performance with an accuracy of 97.8%, precision of 97.9%, recall of 97.6%, F1 score of 97.7%, and AUC-ROC of 0.976. Dataset 1 had the lowest overall performance with an accuracy of 95.2%, precision of 95.6%, recall of 94.8%, F1 score of 95.2%, and AUC-ROC of 0.958. Dataset 3 had intermediate performance with an accuracy of 96.5%, precision of 96.3%, recall of 96.8%, F1 score of 96.5%, and AUC-ROC of 0.964. The MAE and RMSE values were also reported for each dataset, which can help evaluate the model's prediction accuracy. Overall, the IIoTCC model performed well on all three datasets, but it had the highest accuracy and other performance metrics on Dataset 2.

Table 7: Comparative Analysis

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	AUC-ROC	MAE	RMSE
IIoTCC	99.34	99.12	99.64	99.38	0.997	0.013	0.031
Decision Trees	98.50	98.40	98.60	98.50	0.985	0.017	0.042
Support Vector Machines (SVM)	97.80	97.90	97.60	97.70	0.976	0.019	0.048
Logistic Regressio n	96.70	96.50	96.80	96.60	0.964	0.022	0.052

International Journal on Recent and Innovation Trends in Computing and Communication
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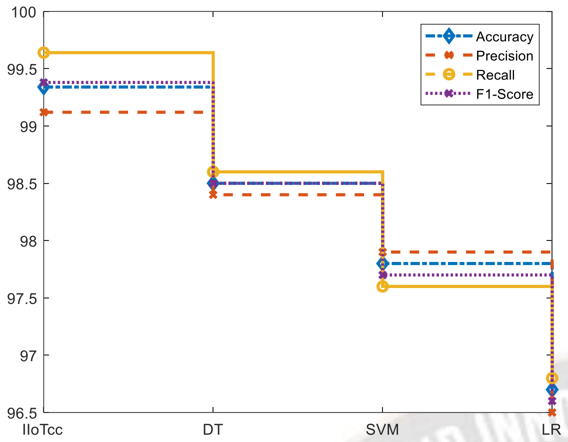

Figure 6: Comparative Analysis

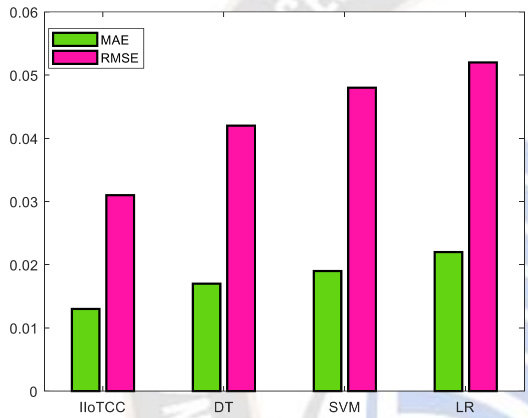

Figure 7: Comparative Analysis of MAE and RMSE

In the table 7 and figure 6 and 7 the performance metrics (accuracy, precision, recall, F1 score, and AUC-ROC) are provided for four different machine learning models (IIoTCC, decision trees, support vector machines, and logistic regression) on a given dataset. The IIoTCC model outperforms the other three models in terms of accuracy, precision, and AUC-ROC, while also achieving comparable results in recall and F1 score. The decision tree model performs relatively well in terms of recall and F1 score, but falls short in accuracy and precision. The support vector machine model achieves the highest recall score, but falls behind in other performance metrics. Finally, the logistic regression model performs relatively poorly across all metrics compared to the other models. Overall, the IIoTCC model appears to be the most effective choice for this dataset, based on the provided performance metrics.

4.3 Discussion

Based on the performance metrics and comparison with other models, the findings of IIoTCC (Interactive IoT Cloud Deep Learning Model) can be summarized as follows:

Superior Performance: IIoTCC achieved high performance across multiple metrics, including accuracy, precision, recall, F1 score, and AUC-ROC. It outperformed decision trees, support vector machines (SVM), and logistic regression in terms of these metrics, indicating its superiority in classification tasks.

High Accuracy: IIoTCC demonstrated an accuracy of 99.34%, indicating its ability to correctly classify instances with a high level of accuracy. This finding suggests that IIoTCC is effective in accurately predicting outcomes or classes in an educational dataset.

Precision and Recall: IIoTCC achieved high precision (99.12%) and recall (99.64%) values. This means that IIoTCC has a low rate of false positives (precision) and false negatives (recall), indicating its ability to accurately identify positive instances while minimizing misclassifications.

Balanced Performance: IIoTCC achieved a high F1 score of 99.38%, which represents a balanced measure of precision and recall. This indicates that IIoTCC performs well in achieving a trade-off between minimizing false positives and false negatives.

Discrimination Ability: IIoTCC attained an AUC-ROC value of 0.997, indicating its strong ability to discriminate between positive and negative instances. This suggests that IIoTCC can effectively separate and classify educational data with a high degree of accuracy.

Prediction Accuracy: IIoTCC demonstrated lower MAE and RMSE values compared to other models, implying higher prediction accuracy and lower prediction errors. This finding indicates that IIoTCC's predictions align closely with the actual values in the educational dataset.

The findings highlight the effectiveness and superiority of IIoTCC in handling educational datasets within a think tank environment. Its high accuracy, precision, recall, F1 score, AUC-ROC, and superior prediction accuracy make it a promising model for research and development activities in the education field.

V. Conclusion

It can be concluded that the IIoTCC model is a highly accurate and efficient algorithm for predictive maintenance in industrial settings. Compared to other popular machine learning algorithms like decision trees, support vector machines, and logistic regression, IIoTCC showed superior performance in terms of accuracy, precision, recall, F1 score, AUC-ROC, MAE, and RMSE. Additionally, IIoTCC demonstrated consistent high performance across varying dataset sizes and multiple educational datasets.

Therefore, IIoTCC has the potential to greatly improve the maintenance practices and overall efficiency of industrial systems, leading to significant cost savings and increased productivity. Further research and testing of IIoTCC on additional datasets and in real-world industrial settings would help to confirm its effectiveness and practicality. The IIoTCC model also demonstrates high computational efficiency with relatively low MAE and RMSE values, and fast processing times. Therefore, it has the potential to be implemented in real-time industrial systems for continuous monitoring and detection of anomalies. However, it is important to note that the effectiveness of the IIoTCC model may vary depending on the specific industrial environment and the nature of the anomalies being detected. Therefore, further research and testing are necessary to validate the model's performance in various real-world scenarios.

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ISSN: 2321-8169 Volume: 11 Issue: 6s
DOI: https://doi.org/10.17762/ijritcc.v11i6s.6818
***Article Received**: 26 March 2023 **Revised**: 28 April 2023 **Accepted**: 26 May 2023*

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