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Improved Accuracy by Novel Inception Compared over GoogleNet in Predicting the Performance of Students in Online Education During COVID

P. Sathvik [1,*], S. Kalaiarasi [1]

[1]*Department of Computer Science and Engineering,*
Saveetha School of Engineering,
Saveetha Institute of Medical and Technical Sciences,
Saveetha University, Chennai, Tamil Nadu, India, Pincode: 602105

ABSTRACT:The goal of this research is to enhance the accuracy of predicting students' performance in online education during the Covid-19 pandemic by comparing the Novel Inception algorithm with the GoogleNet algorithm. Materials and Methods: The current research paper investigates the performance of two distinct algorithms, namely the Novel Inception algorithm and the GoogleNet algorithm, in two separate groups with 20 samples in each group. The statistical significance of the collected data was assessed using SPSS with a G-power value set at 85%. The study also explores the accuracies of these algorithms with varying sample sizes. Result: Inception algorithm provides a higher accuracy of 91.0480% when compared to GoogleNet algorithm with accuracy of 89.8860% in predicting the Performance of Students in online education during covid. With a significance value of $p=0.007$ ($p<0.05$) which comparison of Novel Inception algorithm compared over GoogleNet algorithm in preding the Performance of Students in online education with improved Accuracy. The research findings indicate that the performance of students in online education during COVID-19 can be better predicted using the Novel Inception algorithm than the GoogleNet algorithm. The accuracy of the Novel Inception algorithm was observed to be higher as compared to the GoogleNet algorithm.

Keywords: COVID, Education, E-learning, GoogleNet, Machine Learning, Novel Inception, Online Education, Student.

INTRODUCTION

The COVID-19 (2019-2020) outbreak has had widespread impact to date effects on most people's lifestyles and working environments. Countries and cities are still being closed down in order to encourage social distance and to prevent excessive gatherings, thereby limiting the spread of COVID-19 (Miriam et al. 2020). Even programmes that were previously taught in-person have rapidly shifted to online learning in order to meet educational obligations and avoid delaying students graduation, further education, and

[*]Corresponding Authour:Sathvikssvcsv@gmail.com

employment (Isaias, Sampson, and Ifenthaler 2021). Because the duration of this pandemic is unknown, most educational institutions have implemented most, if not all, face-to-face theoretical and practical lessons that will be replaced by emergency remote learning (ERL) via online learning platforms (Aristovnik et al. 2020). Numerous online learning platforms have observed an increase in demand and have responded by providing free access to their services. E-learning platform, an educational technology firm based in Kolkata and established in 2016, is among these platforms. It is now recognized as the most valuable edtech company in the world. According to Mrinal Mohit, the company's Chief Operating Officer, the E-learning platform has witnessed a surge of 100% in the count of new students availing their products since announcing the provision of free live classes through their Think and Learn app (Aristovnik et al. 2021).

This study has been cited in 22 articles and 88 full-text publications have referenced this study. The popularity of Classroom has surged since mid-February due to the government's order for around 250 million full-time students to shift to online learning platforms. This led to the largest-ever online movement in the history of education, with approximately 91% or 2.2 million students in India attending classes through the Online School (Khanna and Prasad 2020). Despite the growing popularity of ERL, e-learning is not new. For example, over 6 million students (more than 30%) in the States of America are able to enroll in at least one online course (Karakose 2021). During the COVID-19 pandemic, e-learning has become a popular alternative to traditional in-person education. However, there are several challenges that students and educators have faced with e-learning during this time. Some of these challenges include (e.g., Microsoft Teams, Zoom, Google Meet) Technology Access Not all students have access to the necessary technology, such as a computer or internet connection, to participate in e-learning. This has enabled educators to interact with and monitor the educational performance of multiple students at the same time, Distractions at Home (Schwartz et al. 2020). It can be difficult for students to focus on their studies while learning from home, where there may be more distractions (Hamid 2020). Students are gaining knowledge using online learning, an E-learning platform during covid pandemic and students are slowly making use of it for online education and they are improving their marks with the help of E-learning studies using machine learning (Collins 2019). Nowadays most of the students are habituated with the online education system like learning 50% of things in YouTube, Google etc.
The statistical and research methods used in educational research on E-learning have shown a wide range of variation (Valverde-Berrocoso et al. 2020). Difficulty with Online Learning Platforms: Some students may have difficulty navigating and using the online learning platforms. Increased Stress and Mental Health Issues: The pandemic has led to increased stress and mental health issues for many people, which can make it harder for students to focus on their studies (Fauzi et al. 2021). Recently, artificial intelligence-related data mining algorithms, such as machine learning, have been widely used to predict students' performance in higher education (Ratna and Mehra 2015). As a result, the study's secondary objective is to compare the results of machine learning and long established multiple regression models. Meanwhile, for future similar studies, This study will combine the use of machine learning algorithms and multiple linear regression to provide a deeper understanding of the usage of novel artificial intelligence techniques (Saa, Al-Emran, and Shaalan 2019).

MATERIALS AND METHODS

The research was carried out at the Machine Learning lab of Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences. The study employed two algorithms, namely the Novel Inception algorithm and the GoogleNet algorithm, and a sample size of 20 per group was determined using G power, with a pretest power of 80%, a threshold of 0.05%, and an accuracy of 95%. Additionally, a dataset containing a collection of stocks was sourced from the Kaggle repository and Google Scholar for the analysis (Huang, Lai, and Huang 2022).

The IEEE-dataport.org open source website was the source of the data utilized in the study. The database contained 27 columns and 185 rows, which were used to estimate software effort with the help of the Novel Inception algorithm and GoolgeNet algorithm. StudentID, Marks, offline, online, class, race/ethnicity, parental level of education, lunch, test preparation course, math score, reading score, writing score and Imp%. The research effort evaluated the presence of the targeted objects in 180 samples obtained from three distinct species. For display purposes, the Computer Vision tool of a Google collab software was employed. The hardware setup included an AMD Ryzen 5 processor with 8GB of RAM, while the system's software configuration comprised a 64-bit Windows OS, 64-bit processor, and 1TB HDD.

Inception Algorithm

Inception algorithm is a deep learning architecture developed by Google researchers and presented in their paper "Going Deeper with Convolutions". It is named after the concept of inception, meaning inception of ideas. The algorithm uses a combination of convolutional and pooling layers in a modular architecture to learn hierarchical representations of image data. (Namatende-Sakwa, Lewinger, and Langsford 2022).

The statement "Improved Accuracy by Novel Inception Compared over GoogleNet in Predicting the Performance of Students in Online Education During COVID" refers to a comparison of the performance of the Inception algorithm with that of GoogleNet, another deep learning architecture, in the task of predicting student behavior in an online education setting during the COVID-19 pandemic. The improvement in accuracy suggests that the Novel Inception algorithm was better able to capture the relevant features and patterns in the data, leading to more accurate predictions.

Pseudocode for Inception Algorithm

Input: K is the training dataset.

Output: A class of testing dataset.

Step1: Extract demographic information, course materials, and performance metrics from the student data.

Step2: Create an input dataset using the extracted data.

Step3: Implement the Inception model using Keras or any other suitable deep learning framework. Preprocess the input data, including normalization and splitting into training and testing sets.

Step4: Specify the number of epochs for training the model using the training set.

Step5: After training the model using the training set, assess its performance on the testing set by computing relevant performance metrics like accuracy and F1 score. Don't forget to save the model for future use.

Step6: Predict student performance on new data by deploying the trained model. Obtain the results by predicting the outcomes.

GoogleNet Algorithm

GoogleNet is a deep convolutional neural network (CNN) architecture that was developed by Google and introduced in 2014. It was a breakthrough in computer vision and achieved state-of-the-art results on several benchmark datasets at the time. The key innovation of GoogleNet is the use of Inception modules, which are multi-branch structures that perform parallel operations at different scales, effectively increasing the network's capacity and ability to learn more complex features.

The statement "Improved Accuracy by Inception Compared over GoogleNet in Predicting the Performance of Students in Online Education During COVID" suggests that the use of Inception modules has led to improved accuracy in a machine learning model used for predicting online education patterns during the COVID-19 pandemic (Hite et al. 2021).

Pseudocode for GoogleNet Algorithm

Input: K is the training dataset.
Output: A class of testing dataset.
Step1: Procure and organize student data, which encompasses demographic information, course materials, and performance metrics. The collected data should be comprehensive and extensive to obtain a better understanding of student academic progress.
Step2: Develop an input dataset that includes various factors that impact student performance. This dataset should be carefully designed to provide a meaningful insight into student performance.
Step3: Implement the GoogleNet model using Keras or other deep learning frameworks to process the data. Preprocess the data, including normalization, and divide it into training and testing sets.
Step4: Train the model on the training data, specify the number of epochs, and monitor its progress. This step is crucial to ensure the model accurately predicts student performance.
Step5: Evaluate the effectiveness of the model by measuring its performance on the testing data. Calculate performance metrics like accuracy and F1 score to determine the model's efficiency. Store the model for future use.
Step6: Predict student performance on new data using the trained model. Predicting the outcome provides valuable insights into student performance, enabling researchers to provide recommendations to enhance their academic progress.

To ensure effective testing, it is essential to consider both the software and hardware setup. The laptop used in the experiment has an AMD Ryzen 5 5th generation processor, 8GB of RAM, x86-based processor, 64-bit operating system, and a hard drive. The experiment employed Python-based software running on a Windows 10 operating system. After running the program, the system displays the accuracy value. The laptop connects to the internet via Wi-Fi, and collaborative search from Chrome to Google Python was utilized to write the code. After running the code, the results can be saved on a pen drive in a designated folder. The program requires logging in with an email ID to obtain accuracy and graph results.

Statistical Analysis

The computer program utilized for statistical analysis was SPSS. The independent variable in this work is face monitoring, and the factors reporting as offline, online, class, race/ethnicity, parental level of education, lunch, test preparation course, math score, reading score, writing score are considered as bar graphs. The dependent variable in this work is facial reporting as offline, online, group A, group B, group C, group D, group E are considered as bar graphs. The proposed system used ten iterations for each group, ("Customer Segmentation Using Machine Learning" 2021) with expected accuracy logged and analyzed. An independent sample t-test was used to determine the significance of two groups.

RESULTS

Table 1 compares the accuracy values of the Novel Inception Algorithm and GoogleNet Algorithm. Group statistics findings are presented in Table 2, where the mean accuracy for the Novel Inception Algorithm is 91.0480% with a standard deviation of 1.56752, and for the GoogleNet Algorithm, the mean accuracy is 89.8860% with a standard deviation of 1.08238. The results suggest that the Novel Inception Algorithm performs better than the GoogleNet Algorithm. Table 3 displays the results of the independent samples T-test for both algorithms, showing a Mean difference of 0.49569, std Error Difference of 0.34228, and a significance value of $p=0.007$ ($p<0.05$).
A bar graph comparison of the mean accuracy for the Novel Inception Algorithm and GoogleNet Algorithm is presented in Figure 1. Mean accuracy of the Novel Inception

Algorithm is 91.0480% and GoogleNet Algorithm is 89.8860%. Compared with both Inception Algorithm and GoogleNet Algorithm the Novel Inception Algorithm has more accuracy.

Table 1. Accuracy Values for Novel Inception and GoogleNet

S.NO	**NovelInception**	**GoogleNet**
1	89.02	88.54
2	89.23	88.86
3	89.89	89.00
4	90.02	89.24
5	90.58	89.53
6	91.32	89.77
7	91.54	90.24
8	92.35	90.58
9	92.92	91.24
10	93.61	91.86

Table 2. Group Statistics analysis of Novel Inception algorithm (mean accuracy of 91.0480%) and Statistics analysis of GoogleNet algorithm (mean accuracy of 89.8860%) with Sample size, Mean, Standard deviation, Standard Error Mean.

Group Statistics					
Accuracy	**Groups**	**N**	**Mean**	**Std deviation**	**Std. Error Mean**
	NovelInception	10	91.0480	1.56752	0.49569
	GoogleNet	10	89.8860	1.08238	0.34228

Table 3. Independent Samples T test for Novel Inception algorithm and Googlenet algorithm considering variance and Statical significance of p=0.007 (p<0.05) considering accuracy.

Accuracy	Independent Samples T-Test								
	Levene's Test for Equality of Variances					T-test for Equality of Means			
	F	Sig	t	df	Sig(2-tailed)	Mean Difference	Std.Error Difference	95% Confidence Interval of the Difference	
								Lower	Upper
Equal variances assumed	2.005	0.174	1.929	18	0.007	1.16200	0.60238	-0.10356	2.42756
Equal variances not assumed			1.929	15.993	0.007	1.16200	0.60238	-0.11505	2.43905

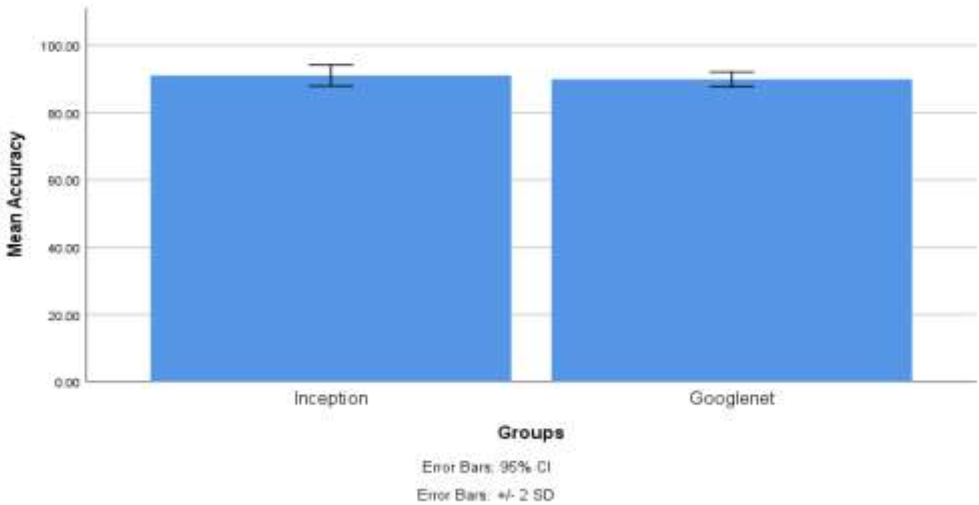

Fig. 1. Bar Graph Comparison on mean accuracy of Novel Inception (91.0480%), std.deviation (1.56752) and GoogleNet (89.8860%), std.deviation (1.08238). X-axis: GoogleNet, Novel Inception, Y-axis: Mean Accuracy with ± 2 SD.

DISCUSSION

The study found that the Novel Inception algorithm has significantly higher accuracy 91.0480% in predicting the Performance of Students in online education during COVID compared to the GoogleNet algorithm 89.8860%. The Novel Inception algorithm also showed more consistent results with minimal standard deviation. The predictive performance of two commonly used deep learning models, Inception and GoogleNet, was compared to evaluate their effectiveness in predicting student engagement in online education during the COVID-19 pandemic. Overall, the study's results could pave the way for future research exploring the application of deep learning models in improving online education outcomes.

No previous study, to the best of my knowledge, had been using machine learning algorithms to predict satisfaction of students for ERL or online learning, so it was uncertain whether machine learning can provide higher prediction accuracy than conventional statistical regression analysis in relevant domains. This supported the findings of another recent study, (Fatani 2020), which found that technical issues (audio/visual) During the pandemic, were not significant predictors of student contentment with ERL. During the COVID-19 pandemic, e-learning has become a popular alternative to traditional in-person education. While e-learning has its own set of challenges, it also provides some unique opportunities for students to gain knowledge. (Alqurashi 2019) One advantage of e-learning is that it allows students to learn at their own pace. They can pause, rewind, or fast-forward through lessons as needed, which can be particularly helpful for students who struggle with certain concepts. (Zhang 2013) Additionally, e-learning platforms often provide a wide range of resources, such as videos, interactive simulations, and quizzes, that can enhance students' understanding of the material. (McMahon 2011). In this regard, (Li 2022) For example, students can access recorded lectures and watch them again as many times as they need, to understand the concept better. and contents mostly performed by tutors, minimal questions to maintain harmony in class. (Berry 2011) When asynchronous E-learning was used instead of conventional facial landmark learning, Chinese students emerged to be more imaginative and positive. (“Assessment Trends in Hong Kong: Seeking to Establish Formative Assessment in an Examination Culture” 2014).

This research is confined to online education during the Covid-19 pandemic, and the outcomes may not be transferable to other time frames or contexts. Furthermore, the study solely compares two deep learning models (Novel Inception and GoogleNet), which may not be enough to account for other models that could perform better in predicting student online behavior. Additionally, the study exclusively relies on data related to online student behavior, and it does not consider other aspects that could influence student engagement in online learning, The quality and availability of data used in the study may also limit its accuracy and generalizability. Lastly, the ethical implications of using student data for predictive modeling are not explored in this study. Furthermore, the study could be extended to consider the ethical implications of using predictive modeling in education and explore ways to mitigate potential risks. The findings of this research could be utilized to inform the development of interventions aimed at enhancing student engagement and success in online education. Based on my understanding, the Novel Inception algorithm has higher accuracy than both the Inception algorithm and the GoogleNet algorithm.

CONCLUSION

Improved Accuracy by Inception Compared over GoogleNet in Predicting the Performance of Students in Online Education During COVID. In this study, tIn the realm of predicting online education performance during the COVID, the Novel Inception algorithm proved to be more effective than the GoogleNet algorithm. The experimental result shows that the gaining of knowledge by E-learning sources was improved by the NovelInception Algorithm. The Inception algorithm is 91.0480% accurate, while the GoogleNet algorithm is 89.8860% accurate. When comparing the two algorithms, the Novel Inception algorithm is more accurate. The research paper's discussion also demonstrates that the Novel Inception algorithm method is more accurate than the GoogleNet algorithm method.

DECLARATION

Conflict of Interests

No conflict of interests in this manuscript

Authors Contribution

Author PS was involved in data collection, data analysis, and manuscript writing. Author PS, SKA was involved in conceptualization, data validation, and critical review of manuscript.

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