HYBRID DEEP LEARNING SYSTEM FOR PREDICTING STUDENTS PERFORMANCE IN ONLINE EDUCATION

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Abstract
Virtual learning has grown rapidly with the help of the internet and modern technology. Many students are taking online courses that allow them to study from anywhere in their own space. Virtual Learning Environments (VLEs) provide high-quality resources and flexibility, but they also have some problems. Many students struggle with staying engaged, managing their own learning, and completing their courses, leading to high dropout rates. Predicting which students are likely to fail can help teachers and schools provide better support and improve teaching methods. This study introduces a new Hybrid Deep Learning (HDL) model to predict student performance. It uses advanced AI techniques, including Enhanced Convolutional Neural Networks (ECNN) and the ResNet model, to analyze student data.

Keywords: Deep learning, online education, student's performance, VLEs, HDL, ECNN

Introduction

Student accomplishments are vital in higher education as there are quality measures of a university's academic success record. Many higher education institutions have established that high-quality education can change students' mental abilities, awareness, and knowledge levels. Teachers seek strategies to increase student accomplishments and enhance teaching process effectiveness. Recent technological advancements and allow instructors to examine and analyze online databases for patterns representing student behaviors and learning. Despite the importance of student performance to the learning process, it is a complicated phenomenon impacted by various elements, including the teaching environment and personal study habits. There are several definitions of student performance and analyses of student successes in their co-curricular activities for learning.

Education

Education is the cornerstone of personal, social, and economic development. It empowers individuals with knowledge, skills, and values necessary to contribute meaningfully to society. Traditionally, education has been delivered through face-to-face instruction in physical classrooms, enabling direct interaction between students and teachers. In the modern world, education is no longer confined to physical spaces. Advancements in technology have introduced new modes of learning, allowing access to quality education across geographical and socio-economic boundaries. This has led to the evolution of various educational models, particularly online education, which has grown rapidly in the digital era.

Online learning has transformed education by offering flexibility and accessibility, but it also presents significant challenges that can impact student success. One major issue is low engagement, where students do not actively participate in discussions, assignments, or online activities. Unlike traditional classrooms, where teachers can directly encourage participation, virtual learning environments often lack real-time interaction and structured support. Many students struggle with distractions, lack of motivation, and poor time management, leading to disengagement and, ultimately, academic difficulties.

Offline Education

Offline education, also known as traditional classroom learning, has been the cornerstone of education systems worldwide for centuries. It involves face-to-face interaction between students and teachers within a structured physical environment such as schools, colleges, or universities. This method offers a disciplined routine, immediate feedback, and opportunities for social interaction and hands-on activities, all of which contribute to the holistic development of a student. One of the major strengths of offline education is the strong sense of community and collaboration it fosters. Students can actively participate in group discussions, peer learning, and real-time clarification of doubts, which often enhances comprehension and retention of knowledge. Additionally, the presence of non-verbal cues and physical gestures helps educators gauge students' understanding and adjust their teaching methods accordingly. However, offline education also has its limitations. It typically requires fixed schedules, physical presence, and significant infrastructure, which can pose accessibility challenges for students in remote or underserved areas. The traditional approach may also struggle to adapt to individual learning styles, making it difficult to provide personalized support at scale. These limitations have paved the way for digital and hybrid learning models that seek to combine the strengths of both offline and online education.

Online Education

Online education has revolutionized the learning experience by making knowledge more accessible, flexible, and scalable than ever before. Through digital platforms, learners can access lectures, assignments, and resources at their own pace, from anywhere in the world. This flexibility is especially beneficial for working professionals, remote learners, and students with varying schedules or personal responsibilities, enabling them to balance education with other commitments. A key advantage of online education is the integration of technology to enhance learning outcomes. Features such as video lectures, interactive quizzes, discussion forums, gamification, and real-time progress tracking provide an engaging and personalized experience for students. Moreover, the ability to analyze large amounts of learner data allows institutions to better understand student behavior, predict performance, and offer targeted support.

Online forums like Reddit's r/learnprogramming or platform-specific discussion boards allow learners to ask questions, share insights, and collaborate with peers globally, promoting community-driven education.

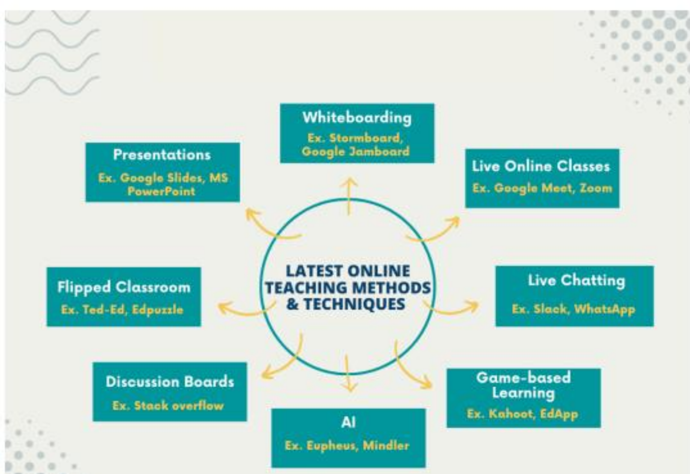

Fig 1: Methods of Online Learning

Students Performance in Online Education

The performance of students in online education is influenced by a variety of cognitive, behavioral, and environmental factors. Unlike traditional classroom settings where instructors can closely monitor student engagement, online learning environments rely heavily on student self-regulation, motivation, and digital literacy. Factors such as time spent on course materials, participation in discussions, consistency in submissions, and assessment scores play a crucial role in determining student success. One of the key challenges in online education is identifying at-risk students before they disengage or drop out. Due to the lack of physical interaction, it becomes difficult for educators to notice early warning signs of poor performance. However, with the advancement of educational technologies and learning analytics, it is now possible to track various metrics—such as login frequency, clickstream data, assignment submissions, and quiz performance—to gain insights into student behavior and performance patterns.

Literature Review

[1] E. Ahn, Y. Gil, and E. Putnam-Hornstein, ‘‘Predicting youth at high risk of aging out of foster care using machine learning methods’’ Youth who exit the nation’s foster care system without permanency are at high risk of experiencing difficulties during the transition to adulthood. To present an illustrative test of whether an algorithmic decision aid could be used to identify youth at risk of existing foster care without permanency. Methods: For youth placed in foster care between ages 12 and 14, we assessed the risk of exiting care without permanency by age 18 based on their child welfare service involvement history. To develop predictive risk models, 28 years (1991–2018) of child welfare service records from California were used. Performances were evaluated using F1, AUC, and precision and recall scores at k %. Algorithmic racial bias and fairness was also examined. Results: The gradient boosting decision tree and random forest showed the best performance (F1 score = .54–.55, precision score = .62, recall score = .49). Among the top 30 % of youth the model identified as high risk, half of all youth who exited care without permanency were accurately identified four to six years prior to their exit, with a 39 % error rate. Although racial disparities between Black and White youth were observed in imbalanced error rates, calibration and predictive parity were satisfied. Conclusions: Our study illustrates the manner in which potential applications of predictive analytics, including those designed to achieve universal goals of permanency through more targeted allocations of resources, can be tested. It also assesses the model using metrics of fairness.

[2] R. Dembo and W. Walters, ‘‘Innovative approaches to identifying and responding to the need of high risk youth,’’ Following a critical review of key issues facing the delivery of effective, cost-attractive services to high-risk youth, and research addressing these experiences, we identify some innovative approaches to identify and respond to the multiple needs of these youth. The importance of providing family services with an ecological focus is stressed. Further, some exciting developments occurring in juvenile assessment centers. involving screening and in-depth assessment, as well as intervention strategies are presented. These innovative developments include for the Tampa Juvenile Assessment Center: 1) a family empowerment intervention service for arrested youth; 2) a family-focused early-intervention, intensive case management service for youth entering a diversion program; and 3) for the Miami-Dade Juvenile Assessment Center, the comprehensive program of research and program development occurring in the context of the National Demonstration Project. We conclude with a discussion of major issues facing the field and the continuing need for a national commitment to help the many troubled youths entering the juvenile justice system.

[3] H. H. Severson, H. M. Walker, J. Hope-Doolittle, T. R. Kratochwill, and F. M. Gresham, ‘‘Proactive, early screening to detect behaviorally at risk students: Issues, approaches, emerging innovations, and professional practices,’’ This article provides a review of current practices and tools used in the proactive screening of behaviorally at-risk students within the context of schooling. While there are many obstacles to the early detection of vulnerable students, some recent developments have helped make educators more receptive to early identification and prevention approaches. In addition to describing current best practices, this article reviews promising innovations in screening and early identification that the authors believe are worth considering and whose structural characteristics, required accommoda tions, and critical features may make them more acceptable to educational users. Implications for the training of school psychologists in the screening and early identification of high-risk students are reviewed and recommendations offered for future research.

[4] M. Yağcı, ‘‘Educational data mining: Prediction of students’ academic performance using machine learning algorithms,” Educational data mining has become an effective tool for exploring the hidden relationships in educational data and predicting students’ academic achievements. This study proposes a new model based on

machine learning algorithms to predict the f inal exam grades of undergraduate students, taking their midterm exam grades as the source data. The performances of the random forests, nearest neighbour, support vector machines, logistic regression, Naïve Bayes, and k-nearest neighbour algorithms, which are among the machine learning algorithms, were calculated and compared to predict the final exam grades of the students. The dataset consisted of the academic achievement grades of 1854 students who took the Turkish Language-I course in a state University in Turkey during the fall semester of 2019–2020. The results show that the

Proposed Model

The architectural design of the proposed Hybrid Deep Learning System is a structured pipeline that enables efficient, data-driven prediction of student performance in online education environments. The system is designed to collect, preprocess, and analyze large-scale educational data using a hybrid deep learning framework that integrates Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and Artificial Neural Networks (ANN). The architecture is modular and scalable, providing both predictive accuracy and interpretability to stakeholders such as teachers, administrators, and policy makers. Each module in the architecture plays a vital role in transforming raw data into meaningful insights. Below is an in-depth explanation of each component of the architectural workflow.

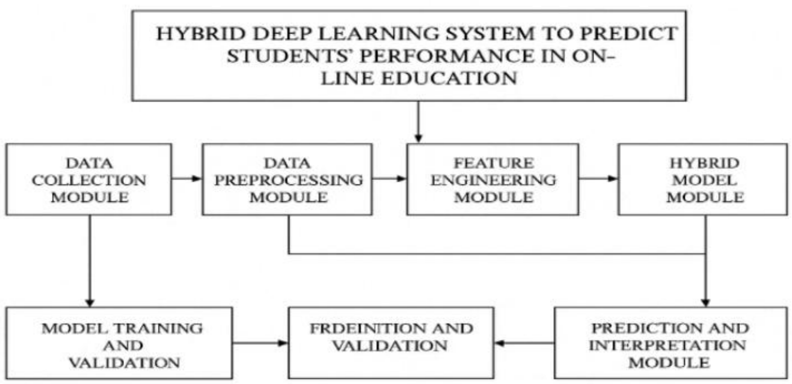

Fig-8: Architectural Design

Convolutional neural networks (CNNs or ConvNets) are used primarily in computer vision and image classification applications. They can detect features and patterns within images and videos, enabling tasks such as object detection, image recognition, pattern recognition and face recognition. These networks harness principles from linear algebra, particularly matrix multiplication, to identify patterns within an image.

Data Collection Module

This is the foundational layer of the system. The Data Collection Module is responsible for acquiring relevant and diverse student data from various sources such as:

a. Learning Management Systems (LMS)
b. Student Information Systems (SIS)
c. Online quizzes, assignments, and exams
d. Behavioral logs (e.g., login frequency, page visits)
e. Communication records (e.g., forum activity, email/chat participation)
f. Demographic data (e.g., age, gender, region

The goal of this module is to ensure that a comprehensive dataset is built, representing both academic and non-academic aspects of student engagement and learning behavior. The quality and breadth of data collected at this stage directly affect the performance of downstream modules.

Data Preprocessing Module

Raw data is often incomplete, inconsistent, or noisy. The Data Preprocessing Module performs critical operations to clean and structure this data. Key tasks include:

a. Handling missing values using techniques like mean/mode imputation or regression-based filling.
b. Data normalization to ensure consistency in feature scaling.
c. Encoding categorical variables using methods like one-hot encoding or label encoding.
d. Outlier detection using statistical or clustering-based approaches.
e. Data transformation such as log-scaling, binarization, or polynomial feature generation. The output of this module is a well-structured, clean dataset ready for analysis and modeling

   Feature extraction:

   Deriving new features from raw attributes (e.g., time-on-task, session frequency, quiz performance trends).

   Feature selection: Choosing the most relevant features using statistical techniques (e.g., chi-square, mutual information) or optimization algorithms such as Butterfly Optimization Algorithm (BOA). Effective feature engineering significantly boosts model performance by directing learning algorithms toward the most predictive patterns.

Hybrid Model Module

At the heart of the architecture lies the Hybrid Model Module, which integrates the strengths of three advanced deep learning models:

Convolutional Neural Network (CNN): Extracts local patterns and spatial features from engagement and performance matrices. Useful for pattern detection in student interaction heatmaps and time-series data representation.

Long Short-Term Memory (LSTM): Captures temporal and sequential dependencies such as semester-wise performance evolution, long-term behavior changes, and engagement sequences.

Artificial Neural Network (ANN): Acts as the final decision-making layer, combining learned representations from CNN and LSTM to output a probability score or class prediction (e.g., high/medium/low performance).

Model Training and Validation

This module takes the preprocessed, feature-engineered data and trains the hybrid deep learning model. Supervised learning is applied using labeled historical data (e.g., student performance outcomes like grades or pass/fail). The training process involves:

Splitting data into training, validation, and testing sets.

Using cross-validation to ensure robustness and avoid overfitting.

Hyperparameter tuning using grid search, random search, or evolutionary strategies.

Backpropagation and optimization using loss functions such as categorical cross-entropy and optimizers like Adam or RMSProp.

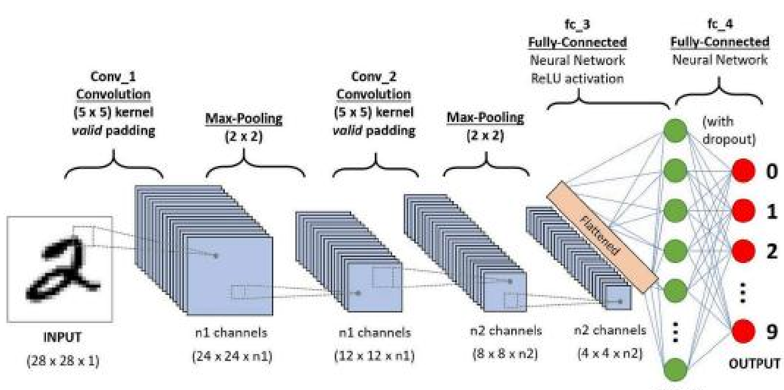

Fig 2: Architecture of CNN

CNNs are a specific type of neural network, which is composed of node layers, containing an input layer, one or more hidden layers and an output layer. Each node connects to another and has an associated weight and threshold. If the output of any individual node is above the specified threshold value, that node is activated, sending data to the next layer of the network. Otherwise, no data is passed along to the next layer of the network.

Recurrent Neural Networks

Recurrent neural networks (RNNs) are typically used in natural language and speech recognition applications as they use sequential or time-series data. RNNs can be identified by their feedback loops. These learning algorithms are primarily used when using time-series data to make predictions about future outcomes. Use cases include stock market predictions or sales forecasting, or ordinal or temporal problems, such as language translation, natural language processing (NLP), speech recognition and image captioning. These functions are often incorporated into popular applications such as Siri, voice search and Google Translate. RNNs use their "memory" as they take information from prior inputs to influence the current input and output. While traditional deep neural networks assume that inputs and outputs are independent of each other, the output of RNNs depends on the prior elements within the sequence. While future events would also be helpful in determining the output of a given sequence, unidirectional recurrent neural networks cannot account for these events in their predictions.

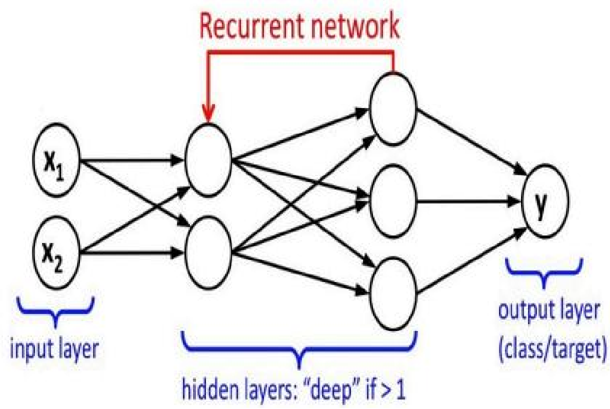

Fig 3:Architecture Recurrent Neural Network

WORKFLOW OF THE SYSTEM

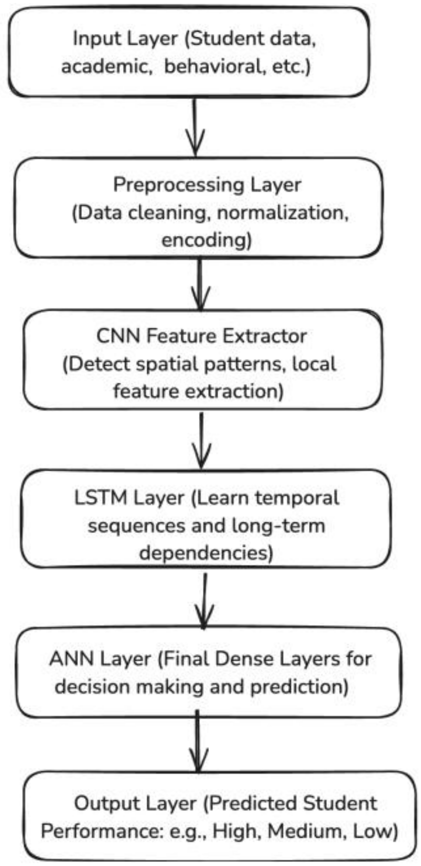

Fig-7: Workflow of the System

The Enhanced Convolution Neural Network (ECNN) is a hybrid deep learning model that integrates the strengths of CNN (Convolutional Neural Network), LSTM (Long Short-Term Memory), and ANN (Artificial Neural Network)to accurately predict student performance by analyzing both static and sequential features from educational datasets.

Results & Analysis

Evaluation metrics are essential tools used to assess the performance and accuracy of machine learning models and algorithms. These metrics provide quantitative measures that enable researchers and practitioners to evaluate the effectiveness of their methods and make informed decisions about model selection and optimization. Moreover, the choice of evaluation metrics depends on the nature of the problem being addressed and the desired outcome. By utilizing a combination of evaluation metrics, practitioners can gain comprehensive insights into the overall performance of their models and make informed decisions regarding their deployment and optimization strategies. These Evaluation metrics play a crucial role in not only validating the performance of machine learning models but also in comparing different models and algorithms. They help in identifying the strengths and weaknesses of a model, guiding the refinement process for better outcomes. Common evaluation metrics include Mean Absolute Error (MAE), Mean Squared Error (MSE), accuracy, and execution time. Each metric serves a specific purpose in evaluating different aspects of model performance, such as prediction accuracy, error magnitude, and computational efficiency.

Class balance along with anticipated outcomes are just two of the many factors that go into choosing the optimal metrics for assessing a classifier's performance in a specific set of data in classification challenges. A classifier may be evaluated on one performance parameter while being unmeasured by the others, and vice versa. As a result, the generic assessment of performance of the classifier lacks a defined, unified metric. This study uses a number of metrics, including F1 score, accuracy, precision, recall, and recall, to assess how well models perform. The subsequent four categories are where these metrics are derived from: True Positives (TP): instances in which both the model prediction and the actual class of the occurrence were 1 (True). False Positives (FP) are situations in which the model predicts a value of 1 (True), but the actual class of the occurrence was 0 (False). True Negatives (TN): an instance in which both the model prediction and the true class of the occurrence were 0 (False). False Negatives (FN) are situations in which the model predicts 0 (False) but the true class of the occurrence was 1 (True).

Accuracy– The mean amount of accurate predictions is used to characterize the accuracy measure. This isn't quite as strong, though, given the imbalanced sample.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

Precision, also known as positive predictive value, gauges the capacity of a model to pinpoint the right examples for every class. For multi-class classification with unbalanced datasets, this is a powerful matrix.

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

Recall – This metric assesses how well a model detects the true positive among all instances of true positives.

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

F1-score – referred to as an F-measure or balanced F-score It might be characterized as a recall as well as precision weighted average.

$$F1_{Score} = \frac{2 * Precision * Recall}{Precision + Recall} \quad (4)$$

Performance Comparison

A comprehensive comparison of the results obtained using different hybrid deep learning techniques was conducted to evaluate the performance of our system. By analyzing evaluation metrics such as Precision, Recall, Accuracy, and F1 Score for both ECNN 1 (ANN + CNN) and ECNN 2 (CNN + LSTM + ANN), we gained meaningful insights into each model's ability to predict student performance effectively. The comparison revealed that ECNN 2 outperformed ECNN 1, demonstrating higher predictive accuracy and a better balance between precision and recall.

Model	Train accuracy	Train Precision	Train Recall	Train F1-Score
ECNN (CNN+ANN)	0.817026744	0.824057538	0.817026744	0.794570028
ECNN (CNN+LSTM + ANN)	0.917234974	0.917438337	0.917234974	0.794570028

Table-2: Comparison of different models results

Graphical comparison of metrics

Fig 11: Graphical view of model comparison

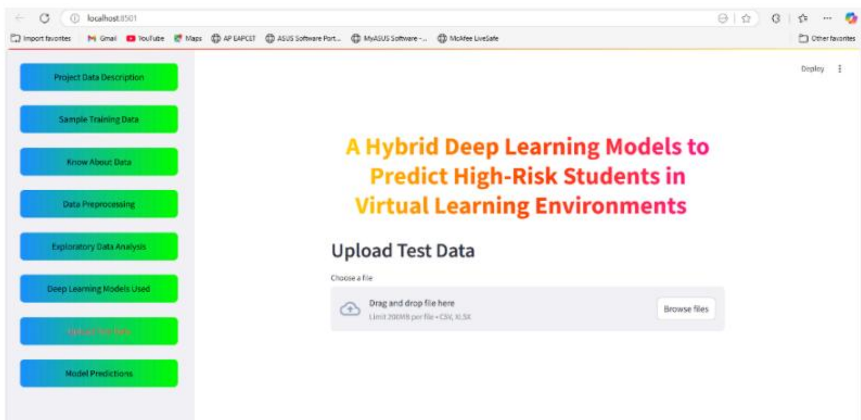

Fig 12: Uploading Test Data

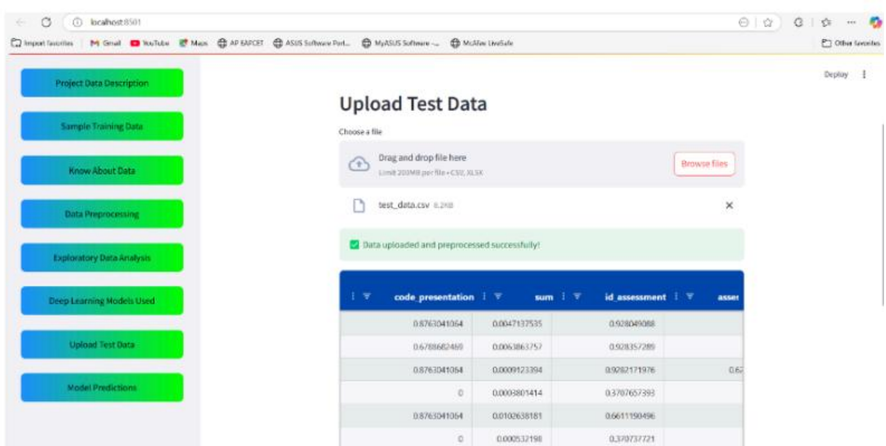

Fig 13: Result of Test Data

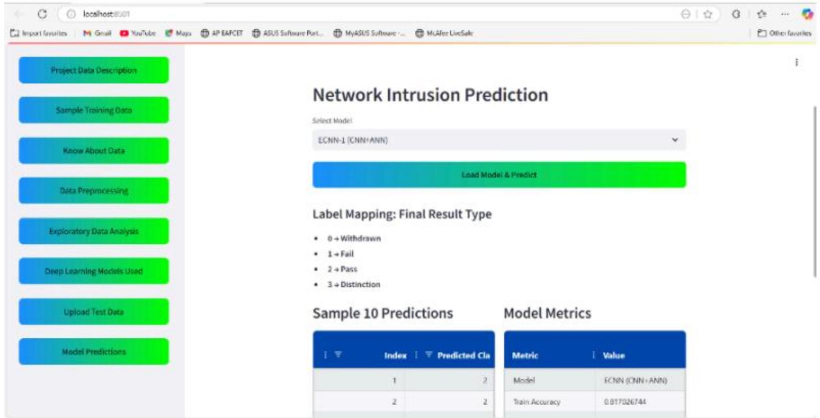

Fig 14:Network Intrusion Prediction 1

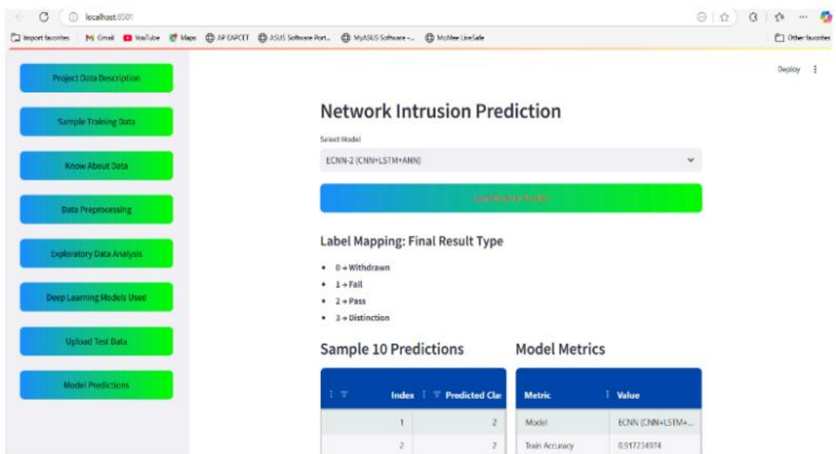

Fig 15:Network Intrusion Prediction 2

Conclusion

In conclusion, the development of a Predictive Hybrid Deep Learning (HDL) System marks a significant advancement in addressing the challenges of online education. By integrating powerful models like ECNN, LSTM, ResNet, and the Butterfly Optimization Algorithm (BOA), the system successfully predicts student performance and identifies those at risk of underachieving or dropping out. Through the analysis of behavioral data, engagement metrics, and academic performance across various phases of a course, the system offers timely insights that allow for early interventions and personalized support. This intelligent, data-driven approach not only empowers educators but also enhances the overall learning experience for students. By proactively addressing performance issues, the system contributes to reducing dropout rates, improving academic outcomes, and creating a more inclusive virtual learning environment. Its ability to adapt to real-time data and process complex student interactions makes it a valuable tool for future-ready education systems.

FUTURE SCOPE

The future of the Hybrid Deep Learning System (HDL) in online education is promising, with significant potential to transform digital learning environments. As virtual education continues to grow, predictive systems like HDL will play a crucial role in identifying at-risk students at an early stage, allowing educators to implement timely and personalized interventions. By integrating diverse data sources such as academic performance, behavioral patterns, engagement levels, and emotional cues, the system can offer a more accurate and holistic understanding of student learning. Advancements in artificial intelligence will enable the model to analyze not only academic metrics but also student emotions, motivation, and attention, promoting a more engaging and supportive learning experience. Future versions of this system can be integrated with adaptive learning platforms that offer personalized content based on student needs and performance trends. Additionally, improved data privacy techniques and secure AI models will ensure ethical use of student information. With scalability and accessibility at the forefront, this technology can be deployed in educational institutions worldwide, including remote and under-resourced areas. Ultimately, the HDL system will contribute to reducing dropout rates, enhancing learning outcomes, and fostering inclusive, data-driven education for all learners.

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