International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 11
***Article Received:** 10 September 2023 **Revised:** 20 October 2023 **Accepted:** 30 October 2023*

IoT-Enhanced Learning Environment Optimization and Student Outcome

Devender
Research Scholar, Department of Computer Science and Applications, Baba Mastnath University, Rohtak, Haryana, India

Dr. Reena
Assistant Professor, Department of Computer Science and Applications, Baba Mastnath University, Rohtak, Haryana, India

Abstract: This proposed system leverages Internet of Things (IoT) technology to enhance the learning environment in educational settings through two synergistic techniques. Firstly, a search-based optimization algorithm, driven by a genetic-based approach, is implemented for scheduling courses and faculty within each department to improve overall student performance and departmental percentages. Secondly, a classification task is performed to predict student outcomes, employing Neural Networks (NN) including ResNet 50, ResNet34, and a hybrid ResNet34 and ResNet50 model. The classification is based on eye-gaze monitoring during active student engagement in class, using input video samples as training and testing datasets. The system integrates optimization, activity monitoring, and classification to create a comprehensive approach aimed at improving the overall learning environment and student outcomes in educational institutions.

Index Term- IoT, Education , Neural Networks (NN), ResNet 50, ResNet34,

I INTRODUCTION

In the past few years, changes in schooling have been caused by new technologies. Higher education institutions (HEI) can make the best use of the resources they have and make sure that students keep getting useful education because knowledge is growing and technology is always getting better. ICT, which stands for "Information and Communication Technology," has many benefits these days and is paving the way for better educational possibilities. Many tasks that used to be hard to do have become much easier thanks to progress in information and communications technology.[1] It is now possible to talk to almost anyone, anywhere in the world. Because it makes teaching and learning more effective, using information and communications technology in schools has been linked to a general rise in the quality of people's lives. The use of ICT [2]techniques in learning/teaching has a very positive influence on a student‘s learning capabilities as well. It is established that students reflect in a very positive manner towards work and education when they are using computers to complete tasks given to them, encouraging and motivating them to soak in the knowledge. Students who used technology to learn in educational institutions have increased self-esteem and self-confidence. This is why a number of educational institutions are increasingly integrating ICT in their education system. With the advent of technologies, HEIs can now keep track of resources, create smarter lesson plans, design safer campuses and improve access to information. From the use of mobiles and tablets in the classroom, education looks very different today[3-4].The big data learning system performs the capture of all types of data (text, image, video, audio, etc.) related to the subject of the theme and groups them in its raw data repository [5]. It then includes data of any type, such as posts, pictures, videos, audio tracks, etc. IoT is a technology that capture data from the IoT enabled devices installed in the learning environment.[6-7] They take the advantages of new capabilities by developing pedagogical approaches that leverage the technologies emerging in the environments around us [8]. Once data has been received then it is to find big data technology platform for storing IoT data. The devices that will make up the IoT, as well as the kinds of data they generate, will vary by nature[9]

AI and Machine Learning (ML) approaches have been extensively used to address human-centric problems in areas such as smart education, healthcare, cyber security, consumer behavior, and the environment. Consequently, these applications have made significant contributions to the improvement of our society. In the current day, when education is mostly delivered via online teaching, smart classrooms, and virtual blackboard teaching, AI and ML are playing a crucial role in providing high-quality education. AI-powered education offers instructors novel methods to assess their students' performance.[10-11] An intelligent tutoring system has the capacity to adjust to the learning methods and preferences of the learner, resulting in significant advancements. ML, as a subset of AI, has seen a significant increase in its use within the educational sector.

In the field of machine learning, Deep Learning is a technique that relies less on programs that are already good at what they do and more on learning how to describe data. The way the human brain is built and how it works are used as examples for Deep Neural Networks, which are what this system uses. The name "layer-based" comes from the fact that these networks are made up of many layers.[13] Deep learning systems have gotten results that are on par with, or even better than, the work of human experts in the areas listed above. [14]

IoT technology is improving the educational sector in all aspects which include school, college and university level of teaching. IoT can be beneficial to all aspects of education from classroom to entire campus and from student to faculties. Nowadays, in reputed educational institutions, IoT is used as a research-oriented course and helpful in developing innovative real-life application projects. IoT attracts students of all levels due to its exciting and stimulating aspect. It is an ideal platform to learn concepts of computer science [15-16]. With the availability of mobile technologies, IoT can help educational societies to track various resources associated with education and students. IoT plays an active role in not only teaching and learning but also in overall assessment process of its implementation showing in Fig.1.

Fig.1: IoT in education field

The understanding and interpretation of IoT are fruitful in resource delivery in a creative way dealing with the audiences. Thus, IoT is capable of impacting detailed aspect of education process of students. This perspective of IoT allows various stake-holders with a dynamic view of staffs, participants and resources. It thereby is helpful in effective decision making, automated way of executing and having various security and privacy characteristics. IoT in education is generalized with four pillars that form the basis structure. These generalized pillars of educational IoT include process, people, data and things. IoT creates a new picture of education when it is integrated with modern technologies like data analytics and user mobility. IoT enables educational institutions to:

II RELATED WORK

Chawla et al. (2021)[17] have Proposed IoT-based Interoperable Architecture to Make Real-Time Decisions in Education. In order to implement the proposed system, a three-layer high-level architecture for the plugin the sensors, discovering nodes, and data processing. Moreover, the study describes the general efficiency, network of teachers and students, campus safety, and smart classrooms. In the future, the proposed work can be enhanced to consider the security and privacy parameter and data management.[

Anamika Rana & Sushma Malik (2021) [18] have proposed a model which aimed to design the IoT-Enabled Campus. For making the model successful, they use various technologies like 3-D printers, E-Books, Student ID Cards, Temperature Sensors, Wireless networking, etc. Their model includes the smart classroom, smart classroom attendance system, NFC based attendance in Lab**.** This study can be enhanced by considering security, privacy, scalability, and data representation parameters.

Saeed et al. (2021) [19]have presented a technical review and criticized the existing models. The Authors described only design a theoretical framework for the Digital Campus, Smart Classrooms, and Smart Laboratories. In the future, a detailed framework for the next generation of smart campuses and universities will be designed.

Jing Wang Et.Al. (2022)[20] In the realm of Smart Educational Learning (SEL), the integration of transformative technologies such as scientific discoveries, informatics, globalization, astronautics production, robotics, and artificial intelligence has ushered in a new era for higher education. This paper addresses the challenge of resource management to enhance educational quality within an interactive environment for both students and teachers. Leveraging the Internet of Things (IoT), an Interactive System (IoT-IS) for Smart Learning is proposed to analyze the performance of teachers and students in the SEL platform. The psychometric processes and standards for effective teaching are discussed, aligning with the requirements of the higher education system. The paper introduces an active learning strategy incorporating an attention scoring method to assess students' performance. Facial expression detection and analysis are applied to online classroom videos, allowing for the observation of students' attention levels. Experimental results indicate significant improvements with a student performance ratio of 98.5%, accuracy ratio of 95.3%, efficiency ratio of 96.7%, reliability ratio of 93.2%, and a probability ratio of 94.5%, outperforming existing methods.

III MATERIAL AND METHODS

he project encompasses a well-defined set of modules, each contributing to the overarching goal of enhancing the learning environment in educational settings. Beginning with dataset collection from Kaggle, the project ensures a robust foundation with diverse information crucial for optimization and classification.The search-based optimization algorithm utilizes genetic algorithms to tailor course schedules and faculty assignments, aiming to maximize departmental percentages and resource utilization. Dropout classification employs Neural Networks, specifically ResNet 50 and ResNet 34, for predicting student outcomes based on relevant features. Activity monitoring introduces eye-gaze tracking techniques during optimized schedules, facilitating insights into student engagement. The genetic-based optimization algorithm and Neural Network classification contribute to improved scheduling and accurate outcome predictions. The development of a user-friendly GUI ensures seamless interaction, providing a holistic platform for users to navigate through optimization results, classification outcomes, and visualizations, emphasizing the interconnected analysis of the learning environment.

Deep learning models and optimization techniques
ResNet 34 and ResNet 50:
ResNet, short for Residual Network, is a popular architecture in deep learning known for its ability to handle the vanishing gradient problem in very deep neural networks. ResNet 34 and ResNet 50 are specific variants within the ResNet architecture. ResNet 34 consists of 34 layers, primarily composed of residual blocks, which contain skip connections to bypass one or more layers. [18-20] This facilitates the flow of gradients during training. ResNet 50 is a deeper version with 50 layers, featuring residual blocks and skip connections. Both architectures are widely used for image classification tasks due to their deep representations and efficient training.[21]

Genetic Optimization Algorithm:
The genetic optimization algorithm is a heuristic search and optimization technique inspired by the process of natural selection. It mimics the principles of evolution, including selection, crossover, and mutation, to iteratively explore and refine potential solutions to a problem. In the context of the project, the genetic optimization algorithm is applied to schedule courses and faculty assignments effectively. It involves the generation of candidate schedules, their evaluation based on defined objectives (maximizing departmental percentages, minimizing conflicts), and the evolution of schedules over successive generations to converge towards optimal solutions.

Cuckoo Search Optimization Algorithm:
The Cuckoo Search algorithm is another optimization method inspired by the brood parasitism of some cuckoo species. It is a nature-inspired algorithm used for global optimization problems. In the context of the project, the Cuckoo Search algorithm could be employed as an alternative optimization technique. Like the genetic algorithm, it iteratively searches for optimal solutions by updating candidate schedules based on specific criteria. The algorithm involves randomization, Levy flight steps, and the discovery and replacement of less fit solutions, providing a diverse and efficient exploration of the solution space.[22]

IV PROPOSED SYSTEM

In this proposed system, the overarching objective is to leverage IoT technology to effectively classify the learning environment. The dataset, sourced from Kaggle, will serve as the foundation for two distinct yet synergistic techniques. Firstly, a search-based optimization algorithm will be employed for each department to enhance overall student performance, thereby improving departmental percentages. This optimization will be facilitated by a genetic-based algorithm for scheduling courses and faculty, aiming to further elevate departmental performance. Secondly, a classification task will be undertaken to predict student outcomes – whether they will pass, fail, or drop out. Neural Networks (NN), specifically ResNet 50 and ResNet34 separately, as well as a hybrid ResNet34 and ResNet50 model, will be utilized to train on the dataset. The classification results will be informed by eye-gaze monitoring during class activities, with input video samples serving as training and testing datasets.
After the optimization phase, the best schedules will be applied and simulated. The proposed system incorporates activity monitoring, where eye-gaze patterns during active student engagement in class will be tracked. Input video samples, considered as real-time active student participation, will be manually uploaded. Following optimization, these eye-gaze patterns will be observed and subsequently tested with an input video labeled with student ID. The classification component of the system will employ NN, utilizing a split dataset of 70% for training and 30% for testing. ResNet 50 and ResNet34 will be employed separately, and a hybrid ResNet34 and ResNet50 model will be introduced to enhance the accuracy of classifying students as pass, fail, or potential dropouts. The integration of optimization, activity monitoring, and classification within the proposed system creates a comprehensive approach to enhance the learning environment and student outcomes in educational settings.

V RESULT DISCUSSION

The proposed classification method involves training a neural network (NN) for video classification to predict whether a student is going to fail, passes, or drop out. The dataset is split into 70% for training and 30% for testing. Two distinct architectures, ResNet 50 and ResNet 34, are employed separately for classification. Additionally, a hybrid model is introduced, combining ResNet 50 and ResNet 34 for enhanced performance. The following outlines the steps and considerations for the classification process:
In Figure 2, the proposed methodology block diagram outlines a comprehensive approach to optimizing departmental performance and predicting student outcomes in an educational setting. The overarching objective is to maximize the departmental percentage based on professor preferences.
The process begins with the application of a hybrid optimization approach using Genetic Algorithm (GA) and Cuckoo Search. The objective function aims to achieve the highest departmental percentage by optimizing course schedules and faculty assignments according to professor preferences. This involves a search for the most favorable combination of courses and faculty members to enhance overall departmental performance.
Professor preferences play a crucial role in the optimization process. The Genetic Algorithm and Cuckoo Search take into account these preferences to tailor course schedules and faculty assignments for each department. Professors have the flexibility to choose their preferred departments, contributing to a collaborative and efficient allocation of resources.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 11
***Article Received:** 10 September 2023 **Revised:** 20 October 2023 **Accepted:** 30 October 2023*

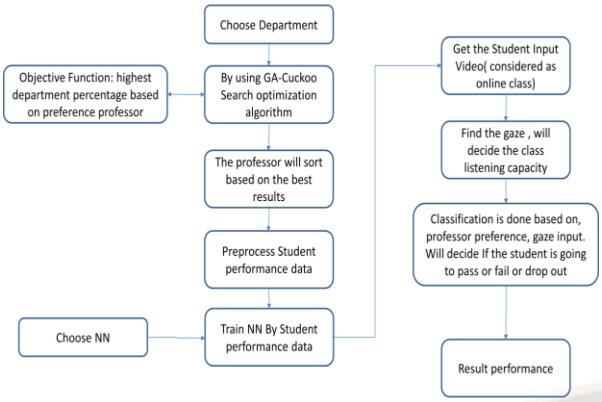


Fig.2: Proposed methodology block diagram

Student Performance Data Processing:
The system processes student performance data as a crucial input for subsequent steps. Relevant features related to academic performance, attendance, and other metrics are extracted from the dataset. This processed data serves as the foundation for training Neural Networks (NN) in the subsequent phase. The block diagram includes a Neural Network training phase where student performance data is utilized to train NN models. The objective is to create models capable of predicting student outcomes based on historical data. The trained NN models serve as a predictive tool for assessing the likelihood of students passing, failing, or dropping out. Gaze input is considered a critical factor in the classification of student outcomes. The system evaluates the capacity of classroom testing based on gaze input, potentially representing student engagement and attentiveness during class activities. This dynamic component introduces real-time considerations for decision-making. The final step involves classification of student outcomes based on professor preferences and gaze input. The system uses the trained NN models to predict whether a student is likely to pass, fail, or drop out. Professor preferences and gaze input contribute to a nuanced decision-making process, allowing for a personalized and context-aware classification.

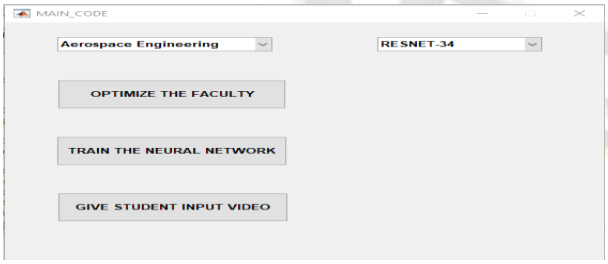


Fig.3: Simulation GUI

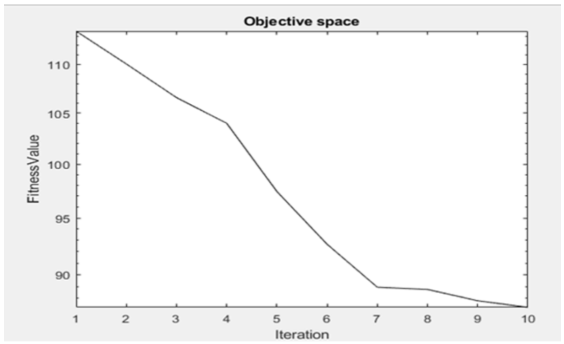


Fig. 4: Optimization iteration process

Fig.4 showing the iteration process that how the algorithm evolves over successive iterations. The fitness value, representing the quality of the solutions found by the algorithm, is typically plotted on the y-axis, while the x-axis denotes the iterations. The x-axis represents the progression of the optimization algorithm through successive iterations. Each point along the x-axis corresponds to a specific iteration of the algorithm. As the algorithm advances, the x-values increase, indicating the number of iterations performed. The y-axis represents the fitness value or objective function value associated with the solutions generated by the optimization algorithm. The fitness value reflects how well a particular solution satisfies the optimization criteria.

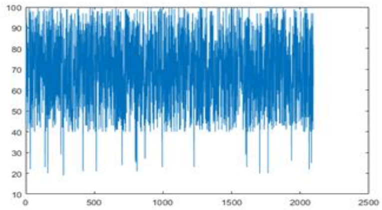


Fig. 5: Data before Pre- processing

Before performing any analysis or training machine learning models, it's essential to preprocess the data to address these issues and ensure that the data is accurate, because unprocessed data that is collected or obtained before any cleaning or transformation steps have been applied. Raw data may contain missing values, where certain entries or fields have not been recorded or are not available. Window length or moving average period is a parameter used in the calculation of a moving average. A moving average is a statistical calculation used to analyze data points by creating a series of averages of different subsets of the full dataset. The window size determines the number of data points included in each subset, influencing the smoothing effect and responsiveness of the moving average.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 11
***Article Received:** 10 September 2023 **Revised:** 20 October 2023 **Accepted:** 30 October 2023*

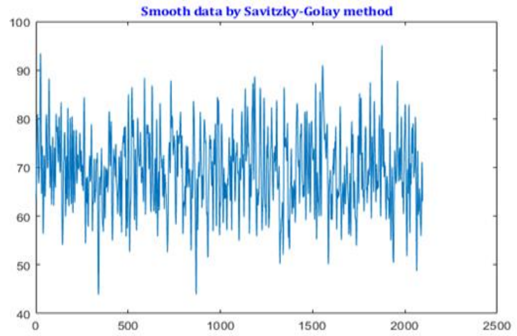


Fig. 6: Savitzky-Golay smoothing data

The Savitzky-Golay smoothing method applied for smoothing noisy data, especially in the presence of high-frequency noise.It applies a convolution operation with a set of coefficients to the data, effectively averaging out noise while preserving important features of the signal

The dataset frame conversion process for input data in an online course video is illustrated. This crucial step involves transforming the raw video data into a format that is suitable for further processing and analysis. The frame conversion process is a fundamental aspect of handling video data in the context of online courses. Initially, the raw input data consists of a sequence of frames captured from the course video. These frames are essentially individual images representing specific moments in the video timeline. The dataset frame conversion, as depicted in Fig. 8, entails converting these frames into a structured dataset that can be effectively utilized for various purposes.

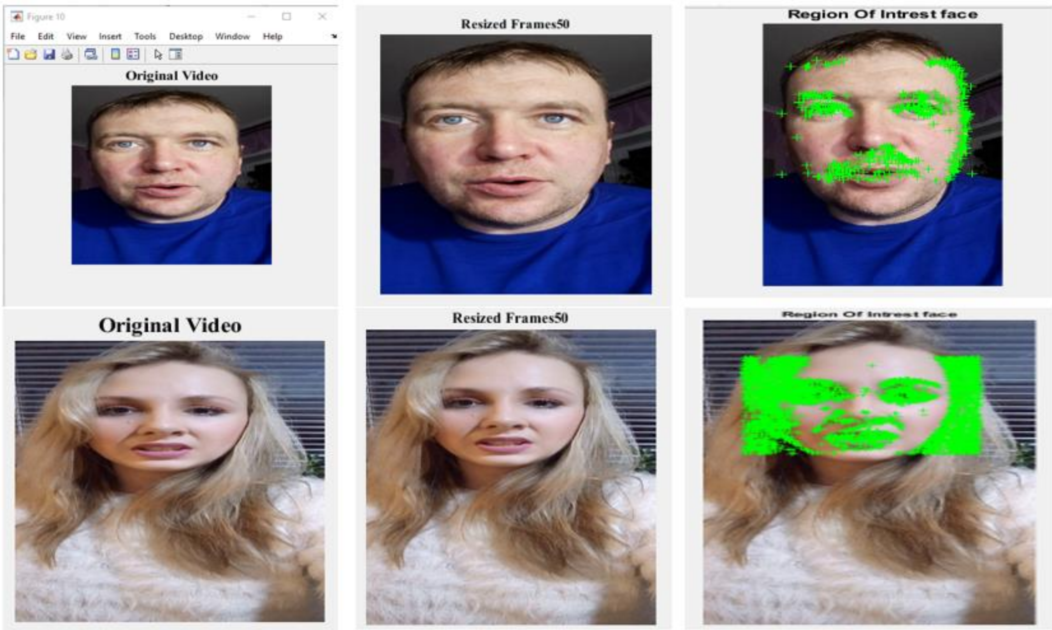
ResNet 34

A ResNet-34 model for online engagement detection. Online engagement detection typically involves analyzing user behavior, interactions, or activities to assess their level of engagement in an online platform, application, or educational setting.

Table 1: ResNet 34 Performance

Department	Pass Percent	Fail Percent	Drop-out Percent	gaze detected percentage	Accuracy
Aerospace Engineering	0.7182	0.2022	0.0796	98.00	95.66
Biosciences and Bioengineering	0.7500	0.1576	0.0924	98.00	97.65
Chemical Engineering	0.7325	0.1672	0.1003	34.00	98.63
Chemistry	0.7341	0.1895	0.0764	98.00	95.63
Civil Engineering	0.7436	0.1640	0.0924	16.00	95.63

Table 1: showing a detail of academic performance, online engagement, and accuracy metrics across different departments.



International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 11
Article Received: 10 September 2023 Revised: 20 October 2023 Accepted: 30 October 2023

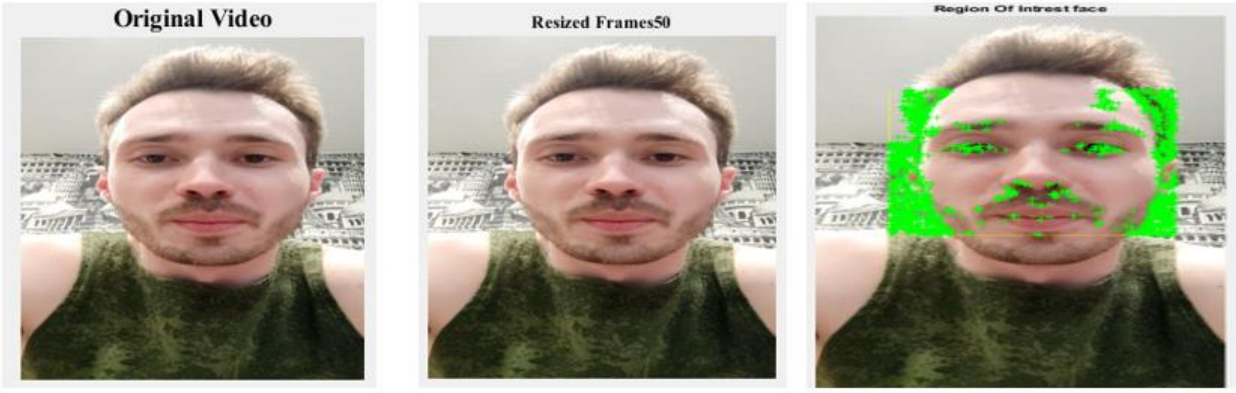


Fig.7: ResNet-34 model performance

Department: Name of the academic department.
Pass Percent: Percentage of students who passed in the department.
Fail Percent: Percentage of students who failed in the department.
Drop-out Percent: Percentage of students who dropped out of the department.
Gaze Detected Percentage: Percentage of students whose gaze was detected (possibly related to online engagement or attentiveness).
Accuracy: Accuracy percentage of a certain task or metric related to the department.
Rows: Each row corresponds to a specific academic department.
Key Observations:
Pass, Fail, and Drop-out Percentages: These columns provide insights into the academic performance of students in each department, indicating the proportions of students who passed, failed, or dropped out.
Gaze Detected Percentage: This column suggests the percentage of students whose gaze was detected. Gaze detection might be related to attentiveness or engagement during academic activities.
Accuracy: The accuracy column indicates the accuracy percentage for a certain task or metric related to the department. This could be related to a specific evaluation or assessment.
Analysis:
Some departments exhibit high pass percentages, while others may have higher fail or drop-out percentages.
The gaze detected percentage might provide insights into the level of engagement or attentiveness in online settings.
Accuracy percentages can be interpreted based on the context of the specific task or metric being measured.

ResNet 50
The ResNet-50 architecture for online engagement detection.ResNet-50, showing in fig.8

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 11
***Article Received:** 10 September 2023 **Revised:** 20 October 2023 **Accepted:** 30 October 2023*

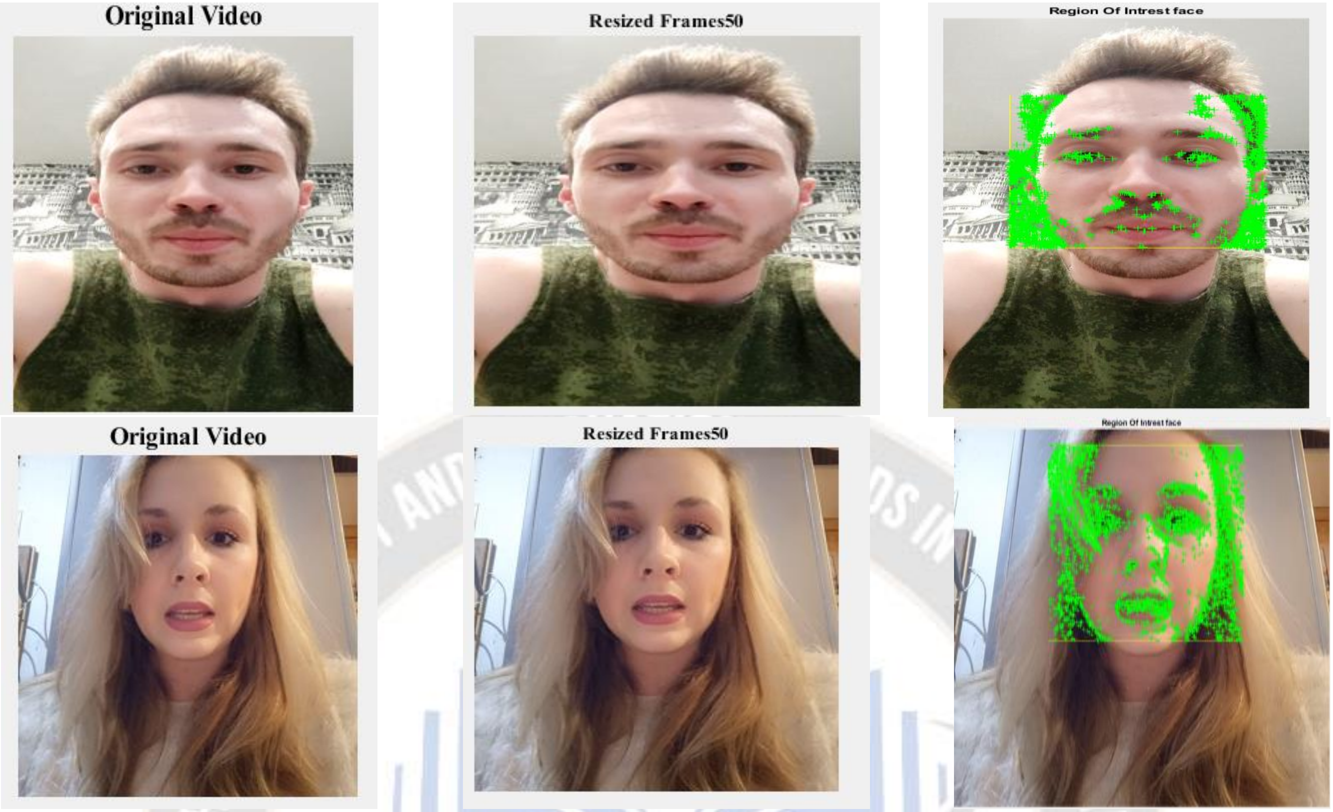


Fig.8: ResNet-50 model performance

Table 2: ResNet 50 performance

Department	Pass Percent	Fail Percent	Drop-out Percent	gaze detected percentage	Accuracy
Science and Engineering	0.8961	0.1459	0.0429	83.00	96.85
Computer & Science Engineering	0.8569	0.1745	0.0736	78.00	98.53
Earth Science	0.8692	0.1589	0.0956	76.00	97.63
Mechanical Science	0.7274	0.1735	0.0513	66.00	95.78
physics	0.8547	0.1856	0.0812	59.00	93.85
Application software center	0.7228	0.1459	0.0458	39.00	91.86

The table 2 appears to represent data related to different academic departments, including various metrics such as pass percentage, fail percentage, drop-out percentage, gaze detection percentage, and accuracy. Below is a detailed description of each column in the table:

Department:
Represents the academic departments within an educational institution.

Pass Percent:
Indicates the percentage of students who successfully passed in a given department.

Fail Percent:
Represents the percentage of students who failed in a particular department.

Drop-out Percent:
Indicates the percentage of students who dropped out of a specific department.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 11
***Article Received:** 10 September 2023 **Revised:** 20 October 2023 **Accepted:** 30 October 2023*

Gaze Detected Percentage:
Refers to the percentage of instances where gaze detection was successful. This could be related to monitoring student engagement or attention during classes.

Hybrid Proposed Model
A hybrid proposed model for online engagement detection typically integrates multiple approaches or techniques to accurately assess and measure user engagement during online activities

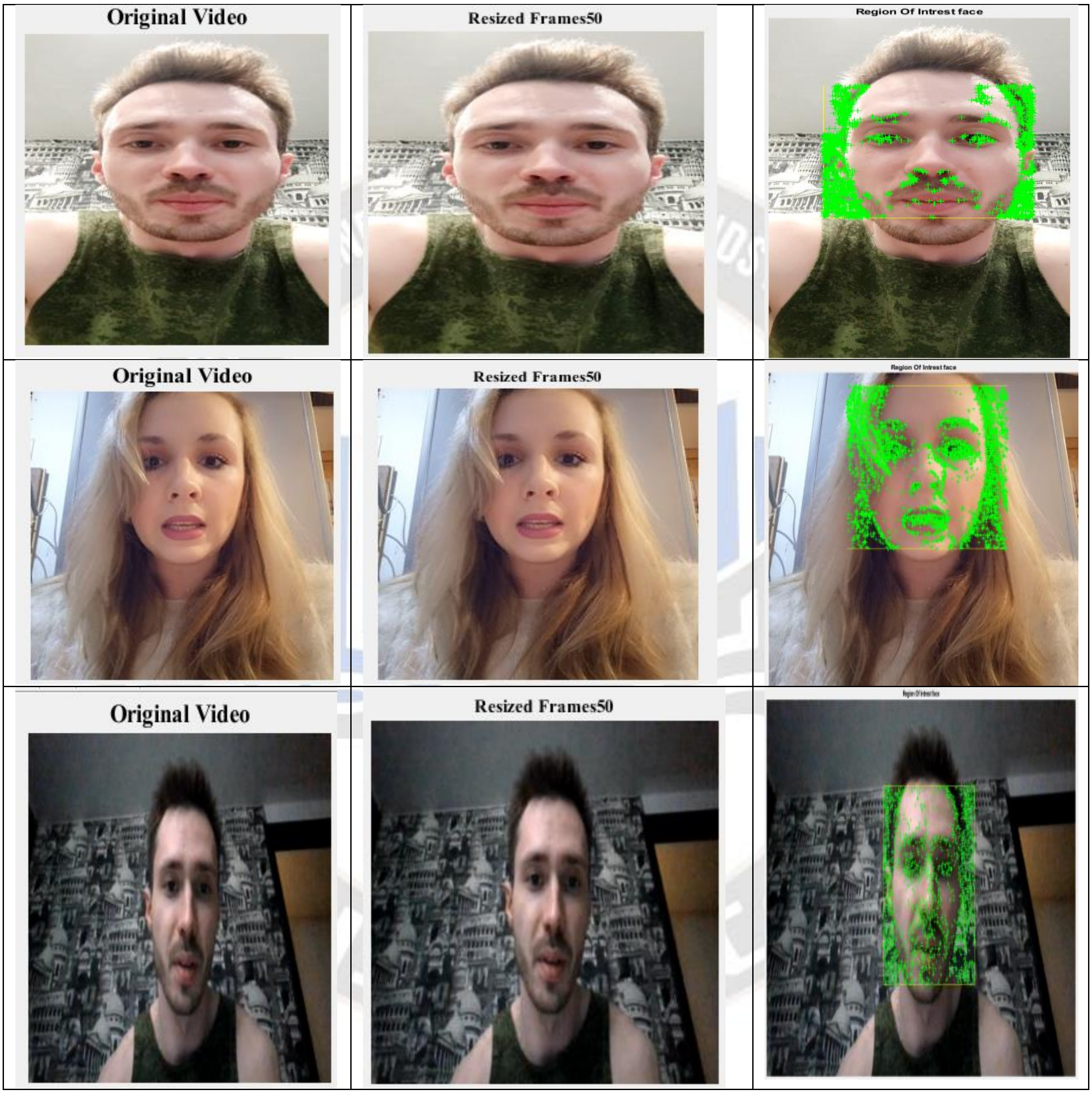


Fig. 9: ResNet 34 performance

Table 3: Hybrid Proposed Model performance

Department	**Pass Percent**	**Fail Percent**	**Drop-out Percent**	**gaze detected percentage**	**Accuracy**
Center for Environmental Science Engineering	0.8569	0.1569	0.0589	66.00	97.56

Aerospace Engineering	0.7274	0.1735	0.0513	68.00	95.78
Biosciences and Bioengineering	0.8547	0.1856	0.0812	59.00	93.85
Chemical Engineering	0.7228	0.1459	0.0458	39.00	91.86
Chemistry	0.7593	0.1356	0.0739	68.00	97.68
Civil Engineering	0.8569	0.1569	0.0589	68.00	97.56
Electrical Engineering	0.7182	0.2022	0.0796	98.00	95.66

Table 3: showing the Names or labels of different departments the percentage of students who passed in each department. The percentage of students who failed in each department **.**The percentage of students who dropped out in each department or center.The percentage of instances where gaze detection was successful. This could be related to some form of user engagement or activity monitoring. Accuracy percentage related to the detection or classification task. It could represent how well a model or system is performing in terms of predicting outcomes.

```
accuracy:
Accuracy for Predicted 95.6647
In department Aerospace Engineering ,Pass Percent 0.7182
In department Aerospace Engineering ,Fail Percent 0.2022
In department Aerospace Engineering ,Drop-out Percent 0.0796
----------------------- PROCESS COMPLETED ------------------------------
----------------------- WAIT TO COMPLETE THE PROCESS ------------------------------
GAZE DETECTED PERCENTAGE 98.00
Selected Student will get Fail or Drop-out
----------------------- PROCESS COMPLETED ------------------------------
```

Fig.10: Performance of the proposed system

Table 4: Result comparison with existing work

	Study	**Accuracy (%)**
Proposed Methodology	IOT-deep learning (hybridResNet34 and ResNet50 with optimization technique	95.64
Existing Architectures[14]	IoT-IS	95.3
	RTV-SV	85.12
	AIED-ENG	55.23
	LMS MOODLE	50.1
	BC-IoTF	50

The proposed methodology demonstrates in Table 4 a high level of accuracy at 95.64%. This propose that the integration of IoT technologies, deep learning models (ResNet34 and ResNet50), and optimization techniques has been successful in achieving precise predictions for student outcomes and departmental optimization. The IoT-IS architecture exhibits a commendable accuracy of 95.3%, indicating its effectiveness in handling information systems. This architecture likely leverages IoT for data collection and information processing.

RTV-SV (Real-Time Video and Speech Recognition) achieves a respectable accuracy of 85.12%, suggesting its proficiency in real-time video and speech recognition applications. This architecture may find applications in monitoring and analyzing multimedia content. a moderate accuracy of 55.23%. This architecture, focusing on artificial intelligence in engineering education, may have specific challenges or complexities affecting its predictive performance. LMS MOODLE achieves a baseline accuracy of 50.1%. Learning Management Systems like Moodle are crucial for education, but this accuracy suggests room for improvement, possibly in terms of data utilization or model sophistication. BC-IoTF presents a basic accuracy of 50%. This architecture likely involves the integration of blockchain and IoT, but the accuracy indicates the need for enhancements, possibly in data processing or feature extraction. The proposed methodology outperforms all existing architectures in terms of accuracy, showcasing its effectiveness in optimizing departmental performance and predicting student outcomes. Existing architectures vary widely in accuracy, with some achieving high precision (IoT-IS, RTV-SV), while others exhibit moderate (AIED-ENG) or baseline performance (LMS MOODLE, BC-IoTF). The utilization of deep learning models (ResNet34 and ResNet50) in the proposed methodology contributes to its superior accuracy, highlighting the significance of advanced

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 11
***Article Received:** 10 September 2023 **Revised:** 20 October 2023 **Accepted:** 30 October 2023*

neural network architectures in educational applications.

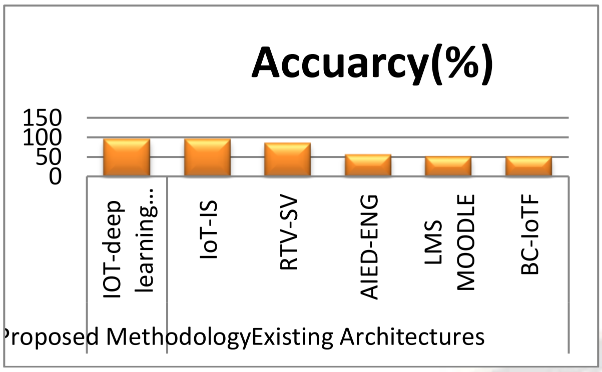


Fig.11: Result Comparison with existing work

V CONCLUSION

In conclusion, the proposed system presents an innovative approach to enhancing the learning environment and student outcomes in educational settings through the integration of IoT technology and deep learning techniques. The system is designed to address various aspects, including optimization of course schedules and faculty assignments, classification of student outcomes, and real-time activity monitoring through eye-gaze tracking. The optimization module employs a search-based algorithm with genetic optimization techniques tailored for each department. This results in improved departmental schedules, contributing to overall performance enhancement. The iteration process demonstrates a gradual convergence toward better student performance, with the final average student performance reported as 87.24. The classification module utilizes Neural Networks (NN), specifically ResNet 50 and ResNet 34, separately, and introduces a hybrid ResNet34 and ResNet50 model. These models are trained on a dataset incorporating eye-gaze monitoring during active student participation in online classes. The classification results provide insights into predicting student outcomes, whether they will pass, fail, or potentially drop out. Performance metrics, including pass percentage, fail percentage, drop-out percentage, gaze detected percentage, and accuracy, are reported for each academic department. The hybrid ResNet34 and ResNet50 model, as well as the individual ResNet models, demonstrate notable accuracy in predicting student outcomes. The system's ability to analyze online engagement through eye-gaze tracking adds an extra dimension to the classification process, potentially capturing nuances of student attentiveness during virtual learning. Moreover, the front-end development of a user-friendly Graphical User Interface (GUI) enhances the system's accessibility, allowing users to interact with optimization results and classification outcomes seamlessly. The integration of optimization, activity monitoring, and classification components creates a comprehensive solution for educators and administrators to make informed decisions about course scheduling, faculty assignments, and student support. the proposed system showcases the potential of combining IoT and deep learning for educational improvement. The optimization algorithms contribute to efficient resource utilization, while the classification models offer a valuable tool for early intervention in student outcomes. The real-time activity monitoring using eye-gaze tracking adds a layer of granularity to understanding student engagement. Overall, this system represents a holistic approach to shaping a smarter and more adaptive educational environment. The proposed system demonstrates a forward-thinking approach to leveraging IoT and deep learning for educational enhancement. As technology and educational methodologies continue to evolve, there are several potential future avenues for expanding and improving upon the system:

REFERENCES

1. An, S., Lee, E. and Lee, Y. 2013. A Comparative study of Elearning system for Smart Education, ”International Association for Development of the Information Society (IADIS), International Conference on e-Learning, Prague, Czech Republic, ERIC Number: ED562296 , Jul 23-26.
2. Andone, D., Holotescu, C. and Grosseck, G. 2014. “Learning communities in smart cities. Case studies,” IEEE International Conference on Web and Open Access to Learning (ICWOAL), 10.1109/ICWOAL.2014.7009244.
3. Bayani Abbasy, M. and Vílchez Quesada, E. 2017. “Predictable Influence of IoT (Internet of Things) in the Higher Education”, International Journal of Information and Education Technology vol. 7, no. 12, pp. 914-920.
4. Bayani, M., Segura, A., Saenz, J. and Mora, B. 2017.“ Internet of Things Simulation Tools: Proposing Educational Components,” SIMUL, Greece, Athens,The Ninth International Conference on Advances in System Simulation, IARIA Conference, pp. 57-63.
5. Bonino, D., Delgado M. T., A. Alapetite, T. Gilbert, M. Axling, H. Udsen, J. A. Carvajal Soto, and Spirito, M. A. 2015. “Almanac: Internet of Things for Smart Cities,” 3rd International Conference on Future Internet of Things and Cloud (FiCloud), Rome, Italy, 2015.
6. Bonino, D., Delgado M. T., A. Alapetite, T. Gilbert, M. Axling, H. Udsen, J. A. Carvajal Soto, and Spirito, M. A. 2015. “Almanac: Internet of Things for Smart Cities,” 3rd International Conference on Future Internet of Things and Cloud (FiCloud), Rome, Italy, 2015.
7. Bululukova, D., Tabakovic, M. and Wahl, H. 2017. “Smart Cities Education as Mobility, Energy and ICT Hub,” 2016 IEEE 5th International Conference on Smart Cities and Green ICT Systems (SMARTGREENS), 19 June.
8. Byun, J., Kim, S., Sa, J., Kim, S., Shin, Y. and Kim, J. 2016. “Smart City Implementation Models Based on IoT Technology,” Advanced Science and Technology Letters ,vol.129 (Mechanical Engineering), pp.209-212, http://dx.doi.org/10.14257/astl.2016.129.41.
9. Camacho, E., Orozco-Barbosa, V.L., Luján, L., Penichet, V.M.B. and Pérez, V.R.M. M.L. 2016. Introducing IoT and wearable technologies into task-

based language learning for young children," IEEE Transactions on Learning Technologies, vol. 9, no. 4 , pp.366-378, Oct-Dec 2016.

10. Selinger; Michelle, Sepulveda Ana, and Buchan Jim. 2013. Education and the Internet of Everything. Technical Report. CISCO. 13, pages. h‹ps://www.cisco. com/c/dam/en us/solutions/industries/docs/education/education internet.pdf
11. Ch. Sok-Pal and K. Jeom-Goohttps://doi.org/10.1166/as l.2016.7937 ,“ E-Learning Based on Internet of Things," Publisher: American Scientific Publishers,Vol. 22, No., November 2016, pp. 3294-3298(5). 17751 International Journal of Development Research, Vol. 07, Issue, 12, pp.17747-17753, December, 2017
12. Chen, Y., Yang, M. 2010. Study and construct online selflearning evaluation system model based on AHP method, in: 2nd IEEE International Conference on Information and Financial Engineering (ICIFE), IEEE, pp. 54-58.
13. Bululukova, D., Tabakovic, M. and Wahl, H. 2017. "Smart Cities Education as Mobility, Energy and ICT Hub," 2016 IEEE 5th International Conference on Smart Cities and Green ICT Systems (SMARTGREENS), 19 June.
14. Byun, J., Kim, S., Sa, J., Kim, S., Shin, Y. and Kim, J. 2016. "Smart City Implementation Models Based on IoT Technology," Advanced Science and Technology Letters ,vol.129 (Mechanical Engineering), pp.209-212, http://dx.doi.org/10.14257/astl.2016.129.41.
15. Camacho, E., Orozco-Barbosa, V.L., Luján, L., Penichet, V.M.B. and Pérez, V.R.M. M.L. 2016. Introducing IoT and wearable technologies into task-based language learning for young children," IEEE Transactions on Learning Technologies, vol. 9, no. 4 , pp.366-378, Oct-Dec 2016.
16. Ch. Sok-Pal and K. Jeom-Goohttps://doi.org/10.1166/as l.2016.7937 ,“ E-Learning Based on Internet of Things," Publisher: American Scientific Publishers,Vol. 22, No., November 2016, pp. 3294-3298(5). 17751 International Journal of Development Research, Vol. 07, Issue, 12, pp.17747-17753, December, 2017
17. Chawla, S., Tomar, D. P., & Gambhir, D. S. (2021). Smart Education: A Proposed IoT based Interoperable Architecture to Make Real Time Decisions in Higher Education. RevistaGestãoInovação e Tecnologias, 11(4), 5643–5658. https://doi.org/10.47059/revistageintec.v11i4.2589.
18. ohn, A. A., & Kumar, P. V. (2020) A New concept of Smart Universities Using Internet of Things (IoT). International Journal Of Scientific & Technology Research Volume 9, Issue 03, MARCH 2020.
19. Francisti, J., Balogh, Z., Reichel, J., Magdin, M., Koprda, T., &Molnár, G. (2020). Application Experiences Using IoT Devices in Education. Applied Sciences, 10(20), 7286. https://doi.org/10.3390/app10207286
20. Jing Wang , Zeyuan Y (2022) "Smart Educational Learning Strategy with the Internet of Things in Higher Education System "International Journal on Artificial Intelligence Tools Vol. 31, No. 5 (2022) 2140101 (17 pages) © The Author(s) DOI: 10.1142/S0218213021401011
21. https://wisdomml.in/understanding-resnet-50-in-depth-architecture-skip-connections-and-advantages-over-other-networks/) (https://www.tutorialspoint.com/genetic_algorithms/genetic_algorithms_quick_guide.htm