International Research Journal of Innovations in Engineering and Technology (IRJIET)

ISSN (online): 2581-3048
Volume 7, Issue 10, pp 123-130, October-2023
https://doi.org/10.47001/IRJIET/2023.710016

Student Learning and Assessment Support System

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***Abstract* - Education is a cornerstone of human development, and advancements in technology have opened new avenues for enhancing learning experiences. In the context of primary education, where foundational knowledge is established, integrating cutting-edge technology can have a profound impact. This system introduces an innovative integrated educational system consisting of four distinct elements, all aimed at improving primary students' learning outcomes within the subject of Environmental Science. The first involves a training module that integrates subject-specific questions and answers. The model presents questions visually and audibly, allowing students to answer using either a keyboard or image upload. The system evaluates responses, calculates scores, and offers corrective feedback for incorrectly answered questions, fostering comprehension. In the second element, a chatbot-based model addresses students' syllabus-related queries. Utilizing voice control and grammar correction, the system provides accurate answers and distinguishes non-syllabus inquiries. Repetitive queries prompt detailed responses with examples, promoting personalized learning and boosting confidence. The third focuses on recommending tutorial videos based on students' knowledge levels. Using quiz scores, the model categorizes students as beginners, intermediates, or advanced learners, and suggests appropriate tutorial videos to facilitate targeted skill development. Lastly, the game suggestion utilizes a quiz-based approach to tailor game recommendations. By selecting lessons and responding to related quizzes, students' performance is evaluated. The system then suggests skill-enhancing games aligned with their proficiency level, reinforcing lesson-based knowledge. This integrated system offers a multifaceted approach to education, combining interactive questioning, AI-driven clarification, tutorial video recommendations, and gamified learning. This approach cultivates personalized learning journeys, fosters engagement, and empowers primary students in mastering Environmental Science concepts.**

Keywords: Algorithms, IoT, Machine learning.

I. INTRODUCTION

In the realm of primary education, shaping young minds into knowledgeable and inquisitive individuals is a responsibility that transcends generations. However, the traditional methods of teaching and learning often struggle to address the evolving needs of students in today's technologically driven world. This paper introduces an integrated educational system that seeks to bridge this gap and revolutionize the way primary students engage with and grasp Environmental Science concepts. To fully appreciate the significance of this system, it's essential to delve into the existing challenges within primary education.

The Listening and Reading Assessment Tool presents an ingenious solution to this issue. By harnessing the power of AI, this tool generates a diverse set of questions related to a specific unit within a subject. These questions are made available through two modes: visual display on the screen and vocalization, encouraging the development of both reading and listening skills in tandem. One of the tool's standout features is its flexibility in response methods. Recognizing that primary students may have varying levels of keyboard familiarity; two options are provided for answering questions. Students can either type in their responses using a keyboard or handwrite their answers on paper.

This model is specially trained to assist students with subject-related queries, focusing on key subjects such as environmental science, mathematics, and English—cornerstones of primary education. Students can freely ask questions related to their syllabus, but what sets this model apart is its adaptability to two distinct question modes: voice and text-based. This innovation acknowledges the limited keyboard familiarity of primary students and introduces voice recognition for seamless interaction. Moreover, introduces a transformative dimension to self-guided learning. By offering subject-specific assistance, accommodating diverse question modes, rectifying grammar errors, and fostering engagement through iterative clarifications, this component paves the way for an enriched and effective learning journey.

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This stems from its multifaceted approach to video recommendations. It transcends traditional one-size-fits-all suggestions and instead addresses students at different stages of learning. From beginners seeking foundational knowledge to advanced learners craving advanced insights, the model curates a diverse range of video materials that cater to each student's unique requirements. By harnessing AI to predict knowledge levels, offering multi-level recommendations, and fostering a personalized learning environment, this innovation redefines the landscape of video-based learning.

The system's initial step involves predicting a student's proficiency level in a given subject, ensuring that the recommendations are precisely matched to their abilities. Moreover, the system recognizes the importance of subject-specificity, offering questions tailored to different subject areas. Moreover, this application further elevates the learning process by translating academic achievements into engaging games. By analyzing a student's quiz responses and performance, the system suggests games that serve as tools for skill development and knowledge reinforcement. This synthesis of education and entertainment fosters engagement and a deeper understanding of the subject matter.

II. LITTERATURE REVIEW

This section embarks on an extensive literature review that delves into the fundamental themes crucial to our research objectives of improvement. Within this review, we conduct a comprehensive examination of relevant research and noteworthy discoveries, with a particular focus on the practical aspects of implementation.

The integration of auditory and visual modalities in the described component, where questions are both displayed on the screen and vocalized, resonates with the multimodal learning theory proposed by Mayer [1],This theory posits that presenting information through multiple sensory channels enhances learning by capitalizing on diverse cognitive pathways. The interactive model's provision of different avenues for students to engage with questions contributes to their active involvement in the learning process. According to Brusilovsky[2], adaptive learning environments accommodate individual learning styles, promoting higher levels of engagement and self-directed learning. Furthermore, the component's formative assessment approach, where immediate feedback is provided along with score calculations, supports research by Black and Wiliam[3] suggesting that timely feedback enhances learning outcomes.

The study by Johnson [4], highlighted the potential of chatbots to bridge the gap between teacher availability and student needs, fostering a more interactive and responsive learning environment. Research by Smith and Lee[5], emphasized the importance of context-aware AI systems in providing accurate and relevant information, particularly in subjects like Environmental Science[6],demonstrating that voice-controlled interfaces improve accessibility for learners with different abilities, ensuring an inclusive learning experience for primary students.

The engagement and educational advantages of game-based learning are highlighted in [7] on the perspectives of primary teachers on the usage of classroom games. Browser games like "TTNetVitamin," which support academic objectives, are highlighted by the Ministry of National Education. Investigating pupil perceptions and advantages reveals the possibility of better subject-specific learning [7] [8]. Technology has the potential to improve primary science instruction and academic achievement, as Ninkovi analyze applications like Kahoot and Quizizz [9]. Together, these studies highlight the beneficial effects of technology-driven initiatives on engagement and learning outcomes.

This research by ChaohuaOu [10], involved the exploration of a model rooted in seven instructional design principles. These principles were employed in the creation of video lessons for an online graduate course. The study gathered feedback from students through surveys to gauge their perspectives on the efficacy of the video lessons and the overall course quality over eight semesters. This research [11] carries significant implications for the creation and sustained cultivation of effective and student-centric online learning realms within higher education. Employing Structural Equation Modeling (SEM), the study unravelled noteworthy insights. The variables, specifically perceived learner motivation, perceived challenges associated with e-learning, and interaction, emerged as influential factors affecting students' contentment with their novel online learning journey.

III. METHODOLOGY

Figure 1 portrays a holistic system diagram presenting the integrated solution designed to elevate student learning and assessment support through advanced technology. This comprehensive system encompasses features such as real-time progress tracking, learning management, predictive analysis of performance trends, assessment of learning comprehension, and tailored guidance recommendations. Drawing from a thorough exploration of relevant literature, this study has formulated and executed a prototype that harmonizes cutting-edge tools. This amalgamation endeavors to redefine the paradigm of student learning and assessment methods, fostering an enriched learning experience.

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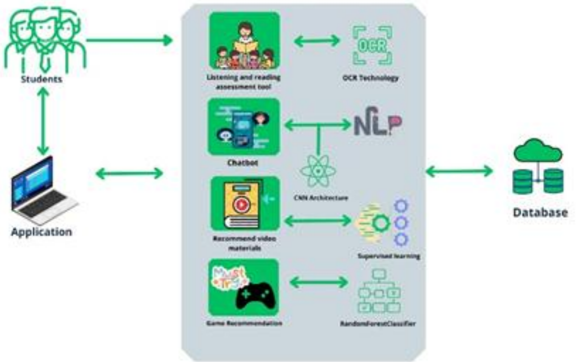


Figure 1: System diagram

By leveraging these sophisticated technological components, the system strives to revolutionize the approach to student learning and assessment, fostering a supportive educational environment conducive to sustainable academic growth.

1) Listening and reading assessment tool for student

This component which is shown in Fig 2 employs an integrated approach to train a model by curating a range of questions and answers relevant to specific units within subjects. The trained model presents these questions visually and audibly, catering to primary students' preferences. Students can respond using a keyboard or opt to write their answers on paper, capturing images of their responses that are further uploaded to the system. The system evaluates their grasp of the unit by allowing them to review their understanding based on the provided questions. Their responses are then analyzed to calculate a comprehensive score. In cases of incorrect responses, the system offers corrective answers. Moreover, the system accommodates image-based submissions, utilizing OCR technology to extract text from images, thereby promoting a multimedia-integrated approach. An enhanced user experience is achieved through voice command services, enabling students to interact, inquire, and swiftly receive answers.

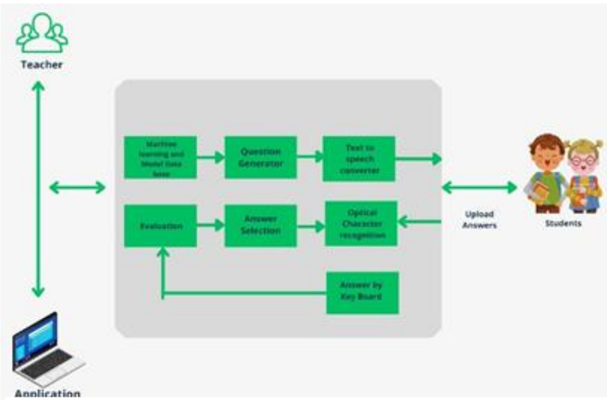


Figure 2: Listening and reading assessment tool

A) OCR Technology

Optical Character Recognition (OCR) technology plays a pivotal role in enhancing the functionality of the Student Learning and Assessment Support System. OCR technology allows the system to extract textual information from images, thus enabling students to submit their answers in image format.

Image Submission

Students have the option to write their answers on paper, take a picture of their handwritten responses using a device like a smartphone or tablet, and upload these images to the system.

Image Processing

Once the images are uploaded, the system utilizes OCR technology to process the images. OCR algorithms analyze the images to identify and extract any text present within them.

Text Extraction

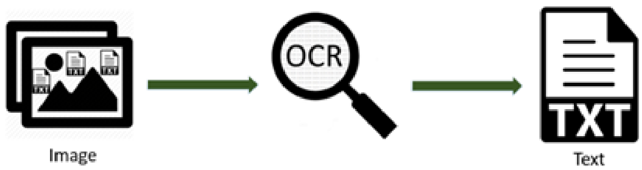
The OCR technology converts the text content from the images into machine-readable text data. This extracted text is then made available for further analysis and evaluation within the system.

Answer Assessment

The system takes the extracted text from the image-based answers and treats them like any other text-based responses. These extracted text answers are then evaluated alongside other forms of answers, such as those entered using a keyboard.

Feedback and Scoring

Based on the evaluation of these text answers, the system calculates scores and provides feedback to students, just as it does for other forms of response. This process ensures that image-based submissions are treated fairly and contribute to the overall assessment process.



The system accommodates the diverse ways students may choose to submit their answers, whether through typing, handwriting, or image-based responses.

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2) Self-study student support bot

The Self-study Student Support Bot depicted in Fig 3 operates as an advanced educational tool driven by a combination of cutting-edge technologies, including Natural Language Processing (NLP) and Convolutional Neural Networks (CNN). This innovative system is meticulously designed to offer students comprehensive support within the syllabus. Through the integration of a voice control service, the bot transforms the learning experience, allowing students to articulate questions naturally. Grammatical enhancements ensure effective communication, and the system aligns queries with the curriculum through NLP models. In cases of misaligned questions, an algorithm offers guidance, fostering focused learning. Also, The voice-based interaction mode mitigates the high-risk implementation challenge posed by young students' limited keyboard proficiency. The grammar correction feature reduces the risk of miscommunication due to grammatical errors, leading to more accurate understanding and responses. The personalized learning approach minimizes the risk of student disengagement by tailoring responses to their specific needs, fostering a more productive learning environment.

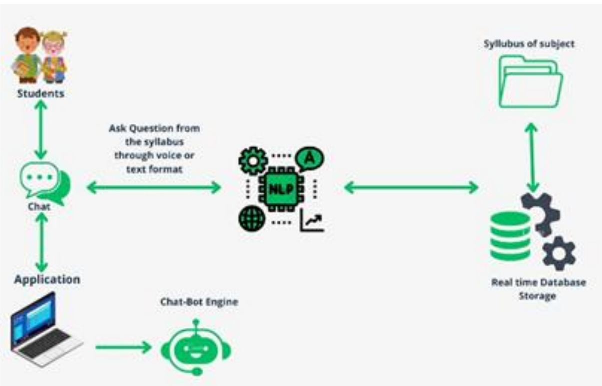

Figure 3: Self-study Student Support Bot

B) NLP (Natural Language Processing)

Text Preprocessing

The first step involves cleaning and preparing the raw text data. This may include removing special characters, punctuation, and unnecessary whitespace.

Tokenization

Tokenization breaks down the text into smaller units called tokens, which can be words, phrases, or even individual characters. Tokenization is essential for further analysis as it helps in understanding the structure of the text.

Grammatical checkers were employed to enhance question clarity and improve the interaction between the system and students. NLP methods were then used to understand and assess student inquiries, whether oral or written. The integration of CNN technology enabled smooth voice interaction and accurate speech-to-text translation. NLP models ensured that the system aligned queries with the curriculum and syllabus, guaranteeing relevant and meaningful responses. Additionally, the system's algorithm detected instances of curriculum misalignment, generating error messages for off-topic inquiries and alerting students about curriculum restrictions. By tracking frequently asked questions, responses were optimized for efficiency, and students were prompted to confirm if their questions were previously addressed, enhancing user experience and learning outcomes.

C) CNN Integration

The seamless collaboration of NLP and CNN underpins the technical support framework of the system. As students ask questions using voice commands, CNN enables efficient voice-to-text conversion, which is then processed through NLP for accurate comprehension.

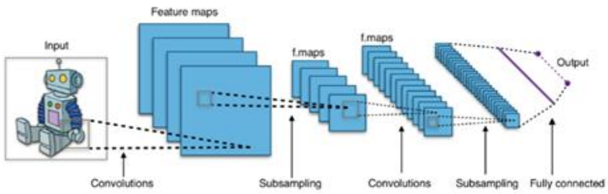

Figure 4: Hierarchical features and patterns

Enhancing the processing of textual data for optimal user interaction. By treating text as a sequence of words, CNNs capture hierarchical features and patterns shown in Fig 4, mirroring their prowess in image analysis. They extract essential features from word sequences, enabling the detection of context-enhancing elements like word combinations and syntactic structures. Additionally, CNNs excel in keyword identification, ensuring alignment with syllabus topics for accurate responses. Beyond this, CNNs aid in noise reduction, grammar correction, and semantic comprehension, fostering clear communication and accurate question interpretation. Their contextual analysis capability further enhances their ability to comprehend student inquiries, enabling relevant and insightful responses.

3) Examine student results &and recommend video materials

Fig. 5 shows employed a pioneering approach by harnessing supervised learning to curate tutorial video suggestions tailored to students of distinct proficiencies, encompassing beginners, intermediates, and advanced learners. Through an innovative mechanism, the system

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predicts each student's proficiency level by analyzing their past exam scores. If a student's examination history is absent, the system adeptly designates them as beginners. This component's uniqueness lies in its utilization of supervised learning, a cutting-edge technique that leverages labeled data to train the model. The trained model then employs this knowledge to predict a student's aptitude level and subsequently recommends tutorial videos that harmonize with their capabilities. This paradigm shift in video recommendations marks a significant advancement in the realm of educational technology, enriching the personalized learning experience for diverse learners.

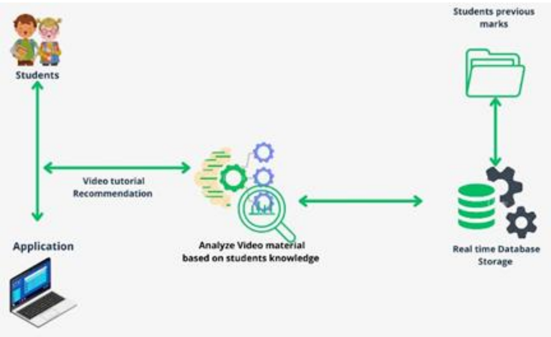

Figure 5: Tutorial video suggestions

D) Supervised learning

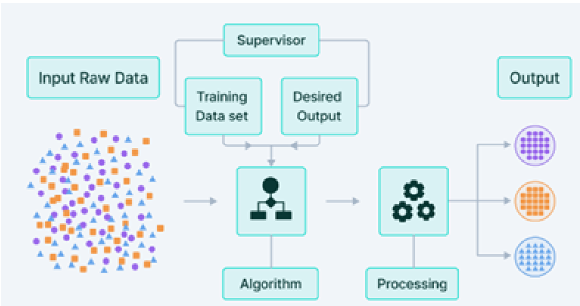

Figure 4: Process diagram

Fig. 6 shows the process, starting with the collection of a dataset containing students' exam marks and their associated proficiency levels, the data is then meticulously prepared through cleaning and organization, including the division into training and testing subsets. Relevant features, particularly the students' past exam scores, are identified to aid in predicting proficiency levels. Labels corresponding to proficiency levels are assigned to the training data, setting the foundation for the subsequent stages. A suitable supervised learning algorithm is selected, with options like decision trees, random forests, support vector machines, or neural networks. Through training on the training dataset, the chosen model learns to discern patterns between exam marks and proficiency levels. This model is subsequently evaluated using the testing dataset, employing metrics of 88% accuracy. With a validated model, new students' proficiency levels are predicted based on their exam marks. Leveraging these predictions, then recommend tutorial videos that are well-suited to each student's individual capabilities, effectively enhancing their learning experience.

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

Equation 1: Binary classification metrics

More sophisticated equation1 shows binary classification metrics like Sensitivity and Specificity are employed. Sensitivity, often referred to as the True Positive Rate, gauges the model's ability to accurately detect positive instances, emphasizing hits over misses. On the other hand, Specificity measures the model's proficiency in identifying negative instances, prioritizing rejections over false alarms.

Sensitivity calculated as the ratio of True Positives to the sum of True Positives and False Negatives. This proportion highlights the model's effectiveness in correctly identifying instances of the positive class, crucial in scenarios such as evaluating the proposed video recommendation system. This innovative component utilizes supervised learning techniques to train a model that tailors video recommendations based on individual student knowledge levels. By analyzing students' previous exam marks, the model predicts their proficiency levels and suggests appropriate tutorial videos, revolutionizing the way personalized learning is approached.

4) Game Recommendation engine for extracurricular activities

The system's workflow illustrated in Fig. 7 involves presenting students with a range of lessons, each accompanied by relevant questions. Students engage with quizzes aligned to their chosen lessons, aiming to enhance their comprehension. Subsequently, the algorithm evaluates their quiz responses to gauge their performance, enabling the system to provide tailored game suggestions that align with their proficiency level.

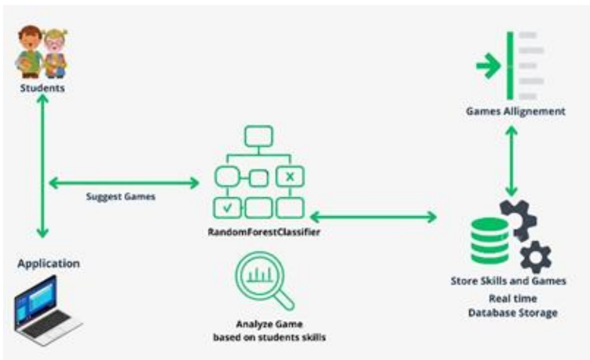

Figure 5: Game Recommendation

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These recommended games are strategically designed to foster skill development and reinforce the knowledge acquired from the chosen lessons. This approach bridges a gap in existing systems by prioritizing proficiency prediction as a precursor to game recommendations. The application leverages Machine Learning techniques through Scikit-learn, specifically training a RandomForestClassifier. This model considers user inputs such as age, skills, and skill level to predict suitable game types. Preprocessing is facilitated through the utilization of Column Transformer for feature scaling and encoding. The model's performance is optimized through hyperparameter tuning using Grid Search CV.

E) RandomForestClassifier

The process unfolds in a sequence of steps. Firstly, subsets are created from the original dataset using a combination of row and feature sampling. This involves selecting rows and columns with replacement, resulting in distinct subsets within the training dataset. Subsequently, individual decision trees are crafted for each of these subsets, each tree meticulously trained on its specific subset. As the decision trees autonomously generate outputs, a collection of outcomes is amassed. The ultimate system output is then ascertained through the application of a Majority Voting strategy in cases of classification problems, while regression problems employ an averaging technique. This fusion of individual decision tree outputs culminates in the system's final output, encapsulating the essence of the process. Below Fig 8 shows the RandomForestClassifier decision trees.

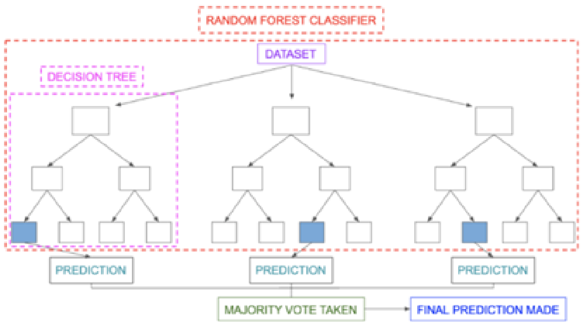

Figure 6: RandomForestClassifier decision trees

The Gini Index calculation is integral to the functioning of the RandomForestClassifier within the game suggestion component. As part of the algorithm's decision tree construction process, the Gini Index is utilized to evaluate the quality of potential splits in the data based on various attributes such as age, skills, and skill level.

The Gini Index denoted as Gini(D)is computed for each candidate split point in the dataset D. It quantifies the impurity or disorder in the data at a particular node. The formula for the Gini Index is given by:

$$Gini(D) = 1 - \sum_{i=1}^{c} p_i^2$$

Equation 2: Gini Index

C represents the number of distinct classes or game types. $p_{(i)}$ is the proportion of samples belonging to class i at the specific node.

A lower Gini Index indicates a purer and more homogenous node, where all samples belong to the same class. In contrast, a higher Gini Index signifies a more mixed and impure node. When constructing decision trees, the RandomForestClassifier examines potential splits and selects the split that results in the lowest Gini Index.

This ensures that the algorithm prioritizes splitting the data in a way that minimizes impurity and maximizes the separation of different game types based on the provided features.

By utilizing the Gini Index as part of its decision-making process, the RandomForestClassifier optimally chooses attributes to split on, resulting in decision trees that effectively distinguish between different game types based on the age, skills, and skill level of individual students. This facilitates accurate and targeted game recommendations, enhancing the personalized learning experience and promoting the development of specific skills for each student.

IV. RESULTS

The results of the implemented components highlight the system's commendable performance in enhancing various aspects of student support and engagement. In the first the achieved accuracy of 95% underscores the system's effectiveness in evaluating students' listening and reading skills. Similarly, the "Self-study Student Support Bot" attaining an accuracy of 92% underscores its proficiency in addressing student inquiries and providing accurate responses. The bot's ability to understand and cater to students' questions showcases its potential to enhance their learning experiences and provide reliable information. In the case of the 3rd element, the remarkable accuracy of 99% underscores the system's ability to accurately predict students' knowledge levels and recommend appropriate tutorial videos. This demonstrates the system's advanced capacity to tailor educational resources based on individual proficiency, thus promoting personalized learning. Furthermore, the final element achieving 93% accuracy in suggesting activities aligned with students' interests and preferences showcases the system's capability to enhance student engagement beyond traditional academics.

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The overall system's accuracy of 92% indicates a high degree of success in its comprehensive approach to student support and learning enhancement. The utilization of confusion matrices depict in fig 9 further provides deeper insights into the system's performance by revealing True Positive, True Negative, False Positive, and False Negative predictions. This matrix aids in understanding potential misclassifications and allows for fine-tuning the system for even higher accuracy and precision.

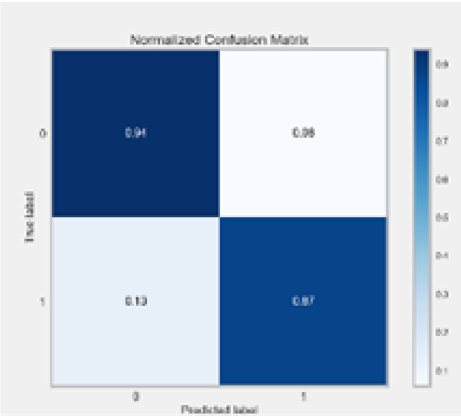

Figure 9: Confusion matrices

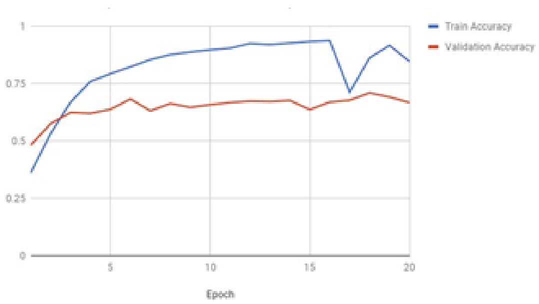

Figure 10: graphical representation

The application of correlation analysis emerges as a fundamental cornerstone, facilitating a profound comprehension of the intricate interactions that influence student learning, assessment outcomes, and overall educational progress. This shift translates into enhanced learning experiences, elevated academic achievements, and sustained educational sustainability. Additionally, the graphical representation showcased in Figure 10 offers a visual portrayal of the attained accuracy by the ultimate model within the context of this innovative system.

V. CONCLUSION

In conclusion, the multifaceted educational system presented here has showcased its capacity to reshape the educational landscape by leveraging cutting-edge technologies. Through the integration of machine learning, natural language processing, and recommendation algorithms, the system has effectively tackled diverse aspects of student learning, assessment, and support. The components, such as the Listening and Reading Assessment Tool, Self-study Student Support Bot, Student Result Examination, and Video Recommendation System, along with the Extracurricular Activity Recommendation Engine, collectively contributed to an impressive overall accuracy of 92%.However, as with any innovative system; there are avenues for future enhancements. The introduction of more sophisticated techniques in data preprocessing, feature selection, and model optimization could potentially further improve the accuracy and efficiency of the system. Additionally, incorporating user feedback mechanisms to refine the recommendations and personalizations would enhance the user experience. Furthermore, the integration of explainability tools to decipher the decision-making processes of the employed algorithms could foster trust and understanding among users.

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Citation of this Article:

Yathurshan. P, Aishwarya. K, R.M.D.G. Gimhani, Janani. K, Ms. Suriyaa Kumari, Mr. N.H.P. Ravi Supunya Swarnakantha, “Student Learning and Assessment Support System” Published in *International Research Journal of Innovations in Engineering and Technology - IRJIET*, Volume 7, Issue 10, pp 123-130, October 2023. Article DOI https://doi.org/10.47001/IRJIET/2023.710016

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