RESEARCH ARTICLE OPEN ACCESS

Student Performance Prediction in OBE Framework Based On Deep Learning Model

Dr.R.Hemalatha [1]
Associate Professor & Head
M.V.Sethu Ramalingam [2]
Ph.D Research Scholar
PG & Research Department of Computer Science
Tiruppur Kumaran College For Women, Tirupur

ABSTRACT

The Outcome-Based Education (OBE) model highlights that every individual has the potential to excel, featuring tailored assessments, accountability for competency-based performance, and more. This paper introduces an OBE platform powered by deep learning, incorporating tailored learning recommendations and evaluations of Classroom quality. It examines the connection between learners' emotional states and their learning efficiency, utilizing a content-based recommendation framework based on Convolutional Neural Networks (CNN) to suggest customized learning techniques. Research findings reveal that the CNN recommendation system excels within the learning resource recommendation platform. The findings also demonstrate that the upgraded algorithm effectively inhibits all actions and shows a notable enhancement in detecting students' performance. These results hold significant importance for advancing the comprehensive integration of contemporary information technology with educational practices and for executing effective OBE.

Keywords: Deep learning, Outcome Based Education, CNN

I. INTRODUCTION

Outcome-Based Education (OBE) is a purpose of which every learner is expected to have achieved their targets. Instead of relying on a single teaching method or evaluation approach, OBE emphasizes that classes, opportunities, and assessments should be integrated to assist students in reaching their aspirations. The role of educators evolves from instructor to trainer, to facilitator, and then to mentor, depending on the objectives being pursued. Responding to the demand for educational transformation, several initiatives have emerged.OBE was designed to help students navigate new challenges, adapt to technological advancements, and apply their knowledge in varied contexts for societal benefit.

This approach to education is grounded in a defined set of educational aims. As learners progress through their studies, they are assigned various learning targets and outcomes, categorized into two groups: Program objectives (PO) and Program learning outcomes (PLO). While PLOs articulate what skills students should possess upon program completion, POs outline the rationale or purpose behind the programs. In practice, the POs of an OBE academic program must align with the needs of employers and other stakeholders, and be consistent with the institution's mission. The PLOs detail the proficiencies that graduates must exhibit based on the POs. Therefore, it is crucial to establish a mapping relationship among the program mission, POs, and PLOs. Students also need to be instructed and evaluated in ways that allow them to fulfill the articulated goals of the PLOs through the curriculum, pedagogical methods, and assessment strategies. In the realm of education, the professional organizations tasked with accrediting engineering programs, such as the Accreditation Board of Engineering and Technology, play a pivotal role in accelerating the transition to the OBE model, that despite the significance of POs and PLOs in the design and accreditation of OBE programs, their definitions and interrelations often remain unclear. In recent years, Learning Analytics (LA) has gained attraction in higher education for various purposes, such as enhancing the learning experience, improving feedback, enriching learning experiences, and aiding decision-making. One effective LA technique is CNN which has been employed to uncover relationships within instructional data.

Consequently, the expected outcomes or competencies that students should demonstrate at the conclusion of their academic program dictate the curriculum content and structure, the instructional strategies employed, the courses offered, the educational setting, and the assessment methods utilized. All curricular and instructional choices are designed based on the most effective means to achieve the desired outcomes. The implementation of an outcome-based curriculum entails a series of steps: Learning objectives are explicitly defined in terms of content, context, and competencies, and these targets are thoroughly described. Various types of program-related data are analyzed through a range of data analytics approaches in each task to derive insights into different aspects of the program. For instance, if a survey of student learning outcomes is employed for data collection, the expertise of professionals along with neural network analysis may be used to predict and evaluate student learning outcomes of an academic program and enhance instructional quality. The researcher applied illuminative evaluation techniques to scrutinize the “matches” and “mismatches” between the intended outcomes in an OBE framework and what actually transpires in classroom instruction.

The following figure depicts the performance is based on the amount of data that is implied in the different sets of deep learning algorithms, that preferably chose the CNN architecture to imply the OBE framework and its structures based on the analysis performance of a student.

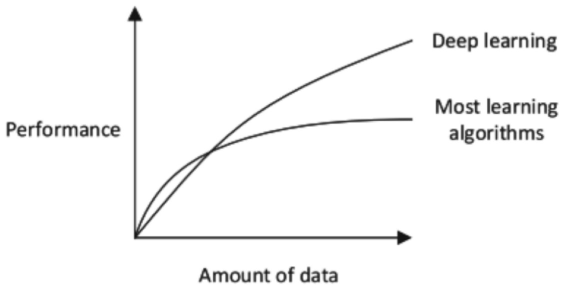

Fig : Performance of Deep Learning algorithms

II. DEEP LEARNING ARCHITECTURE

The types of deep learning networks, including Recursive Neural Networks (RvNNs), Recurrent Neural Networks (RNNs), and Convolutional Neural Networks (CNNs). The RvNN framework is designed for processing entities that possess irregular structures, such as trees or graphs. This methodology produces a fixed-width distributed representation from a variable-sized recursive data structure. The training employs a novel back-propagation through structure learning system, which functions similarly to the conventional back-propagation algorithm while accommodating tree-like configurations. Auto-association trains the network to reconstruct the input layer's pattern at the output layer. In the realm of Natural Language Processing (NLP), RvNNs demonstrate notable efficacy.

A. Recurrent Neural Networks (RNN)

RNNs are a frequently used and well-known algorithm in the field of Deep Learning .Primarily, RNNs are applied within the domains of speech processing and Natural Language Proc Distinct from traditional networks, RNNs operate on sequential data inputs. The embedded structure within the sequential data carries significant information, making this aspect critical for various applications. For example, understanding the context of a sentence is essential for interpreting the meaning of a word within that context. Therefore, RNNs can be regarded as a form of short-term memory, where x signifies the input layer, y represents the output layer, and s indicates the state (hidden) layer. CNNs are generally considered more than RNNs, as RNNs tend to exhibit less feature compatibility in comparison to CNNs.

B. Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) rank among the most renowned and widely utilized architectures in Deep Learning (DL). A primary benefit of CNNs, in contrast to earlier models, is their ability to independently identify crucial features without human intervention which contributed significantly to their popularity. Consequently, we have delved extensively into CNNs by detailing their core components. Moreover, we have thoroughly described the most prevalent architectures within the CNN framework. Deep Learning facilitates learning and classification in a streamlined manner. Recently, DL has emerged as an exceptionally favored category of Machine Learning (ML) algorithms due to the immense advancements and growth in the realm of big data. It remains a field of ongoing innovation, yielding improved performance across numerous machine learning applications and enhancing the progression of various learning domains.

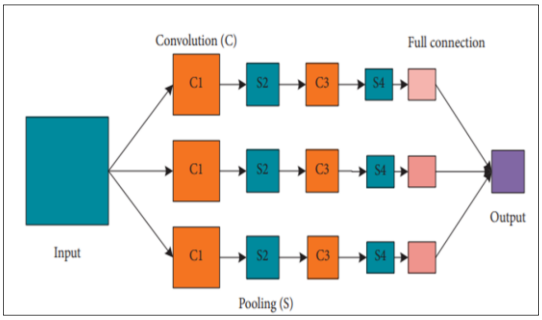

Fig. 1 CNN Layers

C. Advantages of CNN architecture:

The advantages of adopting CNNs as compared to conventional neural networks in the realm of computer vision are outlined as the primary rationale for considering CNN is the weight sharing characteristic, which minimizes the number of trainable parameters in the network, thereby enhancing the network's ability to generalize and prevent overfitting.

Simultaneously learning the layers responsible for feature extraction alongside the classification layer ensures that the model's output is both structured and highly dependent on the features that were extracted. Implementing large-scale networks is considerably more straightforward with CNNs than with traditional neural networks.

III. CNN Layers

The structure of a CNN comprises multiple layers (or multi-building blocks). Each layer within the CNN structure, as well as its function, is elaborated upon below.

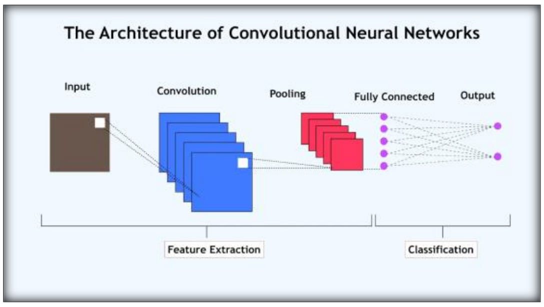

Fig. 2 CNN Architecture

Convolutional Layer: The convolutional layer stands out as the most crucial element in CNN architecture. It is made up of a set of convolutional filters (referred to as kernels). The input image, portrayed as N-dimensional metrics, is convolved with these filters to produce the resulting feature map.

Kernel definition: The kernel is described as a grid filled with discrete values or numbers. Each value is designated as a kernel weight. Initially, random numbers serve as the kernel weights at the start of the CNN training process. Additionally, various methods exist for initializing the weights. Subsequently, these weights are modified during each training epoch; thus, the kernel learns to identify important features.

Convolutional Operation: The format of the CNN input is defined initially. The traditional neural network accepts input in vector format, while the CNN accepts inputs as multi-channeled images.

IV. CONCLUSION

In conclusion, it is essential to include a brief discussion synthesizing all relevant information compiled throughout this comprehensive research. Following this, a detailed analysis is presented to wrap up our review and highlight potential future directions in program outcome and course outcome. DL is already encountering challenges in modeling multiple intricate data modalities simultaneously. In the latest DL advancements, a common method is multimodal.Deep Learning necessitates large datasets (with labeled data being preferable) to accurately predict unseen data and to train the models.

This obstacle becomes particularly acute when real-time data processing is a requirement or when datasets are limited (as is frequently the case with healthcare data). To address these challenges, TL and data augmentation have been the focus of research in recent years.While ML is gradually shifting towards semi-supervised and unsupervised learning to handle real-world data without extensive manual labeling, many prevalent deep-learning models still employ supervised learning. The performance of CNN is significantly impacted by the selection of hyper-parameters. Even minor adjustments to the hyper-parameter values can lead to substantial variations in overall CNN performance. Hence, meticulous parameter selection remains a crucial aspect to consider during the development of optimization strategies. Program Outcomes are also achieved through the direct and indirect methods. The PO attainment is calculated by using the predefined CO/PO matrix and the value of Final CO attainment for the subject.

REFERENCES:

1. Yogeswari, Suppiah and Rajermani, Thinakaran (2022) A Review on the Attainment of Outcome-Based Education Using Educational Data Mining. Journal of Data Science, 2022 (03). pp. 1-11. ISSN 2805-5160.
2. Viet Anh Nguyen, Quang Bach Nguyen, Vuong Thinh Nguyen, A model to forecast learning outcomes for students in blended learning courses based on learning analytics, (2021) 35–41.
3. Amirah Mohamed Shahiria, Wahidah Husaina, Nur'aini Abdul Rashida, A Review on Predicting Student's Performance using Data Mining Techniques, (2019) 414 – 422.
4. H. Najayudin, A. Al-Bdarnath and J.Naduri "Accreditation Software for OBE", 2020 19th International Conference on Information Technology Based Higher Education and Training, pp. 5-9,Jan 2021.
5. Zhang, S., & Liu, Q. (2021). Investigating the relationships among teachers and Education, 134, 145-155.