Previous research highlights significant advances in using clickstream data to predict student performance in MOOCs. A novel self-supervised learning framework effectively models learner behavior, enhancing prediction accuracy and facilitating early intervention strategies. Extensive testing on real-world datasets confirms the framework's effectiveness, with notable results on the Xutangx and KDDCUP datasets.Zhang et al. propose a hybrid deep neural network utilizing CNN, SE-Net, and GRU to predict MOOC dropout within 30 days based on early clickstream data, demonstrating improved accuracy over baseline methods on the KDD Cup dataset [1]. Ding et al. propose using a modified auto-encoder with LSTM in an unsupervised learning framework to enhance feature learning from MOOC student clickstream data, improving prediction accuracy by up to 17% and reducing overfitting [2]. The text discusses a flood resilient system using AI/ML, IoT, and GIS for enhanced flood forecasting, impact assessment, and resource allocation, aiming to improve disaster preparedness and response strategies [3]. Mubarak et al. propose CONV-LSTM, a model integrating CNNs and LSTMs, to predict student dropout in MOOCs. It employs a cost-sensitive loss function to address class imbalance, enhancing prediction accuracy over traditional methods [4]. Yin et al. investigated the high dropout rates in MOOCs using Natural Language Processing techniques, specifically attention mechanisms and conditional random fields, within a novel neural network, demonstrating the effectiveness of this approach through extensive experimental results [5]. Amoudi et al. propose a novel framework using NLP and self-supervised learning to enhance prediction of student performance in MOOCs through clickstream data analysis. Experiments demonstrate up to 80.91% accuracy and 87.42% F1-score, indicating significant improvements in predictive models [6]. Chu et al. investigate student performance prediction using clickstream data, employing time-series learning, self-supervised pre-training, and clustering-guided meta-learning. This approach significantly enhances prediction accuracy and provides insights into student learning behaviors [7]. Scarlatos et al. propose Process-BERT, a framework that uses BERT-type objectives to learn representations from diverse educational process data. It pre-trains on sequential data and fine-tunes on tasks like outcome prediction, enhancing performance and interpretability on real-world datasets [8]. Amoudi et al. propose a novel NLP-inspired self-supervised learning framework to predict MOOC student performance using clickstream data, demonstrating improved predictive accuracy and effectiveness for early intervention, with F1-scores exceeding 80% [9]. The document lacks an abstract and primarily includes administrative details such as the title, author, committee members, and approval information for a dissertation on Representation Learning on Unstructured Data. Additional content is required for a comprehensive summary [10]. Yu et al. used MOOC clickstream data and machine learning algorithms, including KNN, SVM, and ANN, to predict student learning outcomes, finding ANN most accurate. They demonstrated that video viewing correlates with outcomes and categorizing videos by content enhances prediction models [11]. Liu et al. propose a novel student performance prediction framework in online learning systems, integrating student behavior and exercise features with a fusion attention mechanism. Utilizing machine learning and a recurrent neural network, their method achieves 98% accuracy, surpassing previous approaches [12]. Ding et al. propose a transductive transfer learning approach using auto-encoders for MOOCs, enhancing predictive models by organizing clickstream data temporally. This method improves dropout prediction across various MOOCs by learning common predictive features [13]. Wang et al. propose a deep neural network model combining Convolutional and Recurrent Neural Networks to predict student dropout in MOOCs by automatically extracting features from raw data, showing results comparable to traditional methods [14]. Adnan et al. developed a machine learning model, specifically a Random Forest algorithm, to predict at-risk students in online courses. The model, analyzing engagement, assessments, and time variables, achieved up to 91% accuracy, facilitating early interventions to improve student performance and reduce dropouts [15]. Qiu et al. developed a convolutional neural network model for predicting student dropout in MOOCs, integrating feature extraction and classification, and outperforming traditional methods in precision, recall, F1 score, and AUC on public datasets [16]. Yang et al. developed a novel method using time series neural networks and video-watching clickstreams to predict student grades in MOOCs, significantly outperforming traditional models and enabling early intervention for struggling students [17]. Zheng et al. propose the FWTS-CNN model, which combines feature weighting and time series analysis within a CNN to enhance dropout prediction in MOOCs. This model achieves over 87% accuracy on the KDD Cup 2015 dataset, significantly improving by 2% over traditional CNNs [18]