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Optimizing Video Streaming Quality with DBN-Based ABR Prediction Models

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ABSTRACT
The rising demand for seamless and high-quality video streaming has intensified the need for intelligent Adaptive Bitrate (ABR) algorithms that can dynamically respond to fluctuating network conditions and user preferences. Traditional ABR techniques often rely on rule-based logic, which lacks the flexibility to handle complex and real-time network scenarios, leading to frequent buffering and degraded Quality of Experience (QoE). This research work aims to compare the model's performance to existing ABR methods (CNN) by evaluating metrics such as buffering time, video quality, accuracy, precision, recall, and F1-score to measure improvements in streaming quality and user satisfaction. The scope of the study will involve the design of the DBN architecture, optimization of its hyperparameters for improved prediction accuracy, and the integration of the model into a streaming framework. A rich dataset encompassing network latency, bandwidth, packet loss, user behavior, and video playback characteristics was preprocessed, normalized, and balanced using the Synthetic Minority Oversampling Technique (SMOTE). The DBN and CNN models were trained to predict optimal bitrate transitions, aiming to reduce rebuffering and enhance video quality. Evaluation was conducted using key performance metrics, including accuracy, precision, recall, F1-score, buffering time, and video quality. Results show that the DBN model outperformed CNN, achieving 93% accuracy, 94% precision, 92% recall, and 93% F1-score, alongside reduced buffering time and improved video quality consistency. These findings demonstrate the effectiveness of DBNs in delivering robust and adaptive streaming performance and highlight their potential as a scalable solution for future intelligent ABR systems.

Keywords:
Adaptive Bitrate Streaming,
Deep Belief Networks,
Peer-to-peer video Streaming.

INTRODUCTION

With the exponential rise in internet traffic driven largely by video streaming services, ensuring a smooth and high-quality viewing experience has become a major challenge. Adaptive Bitrate (ABR) algorithms play a pivotal role in addressing this issue by dynamically adjusting video quality based on real-time network conditions. However, current rule-based ABR approaches often fail to cope with the complexity and variability of modern streaming environments, leading to frequent buffering, resolution switches, and degraded user satisfaction (Souane et al., 2023).

Recent developments in artificial intelligence, particularly deep learning, have introduced promising alternatives for improving ABR performance. Convolutional Neural Networks (CNNs) and Deep Belief Networks (DBNs) are among the deep learning models being explored to enable intelligent bitrate prediction and enhance the Quality of Experience (QoE). CNNs are effective in capturing spatial patterns from structured input data (Darwich & Bayoumi, 2024; Farahani et al., 2024). These models have shown potential in reducing buffering time, improving video quality consistency, and adapting to user behavior in real time.

Despite existing research in this area, there remains a gap in optimizing algorithm and comparative analysis between CNN and DBN-based ABR models within dynamic and heterogeneous environments such as Peer-to-Peer (P2P) streaming systems. Moreover, while CNNs have been widely applied,

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DBNs offer computational advantages and flexibility, especially where labeled training data is limited (Peroni & Gorinsky, 2024). This study aims to design, implement, optimize and evaluate CNN and DBN models for ABR streaming, comparing their performance across key metrics such as accuracy, precision, recall, F1-score. The research gap identified in the current landscape of adaptive bitrate (ABR) algorithms stems from the limitations of existing methods, particularly in dynamic environments such as hybrid Content Delivery Networks (CDNs) and Peer-to-Peer (P2P) systems. While current algorithms like Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and Recurrent Neural Networks (RNNs) have made strides in addressing bitrate adaptation, they often struggle with high computational complexity and inefficiencies in managing both short- and long-term dependencies. Moreover, these algorithms typically require extensive labeled datasets for training, which may not always be available, thus hindering their applicability in real-world scenarios. Consequently, there is a critical need for innovative approaches that can effectively model complex patterns in network data without the associated drawbacks of existing techniques. This research proposes exploring Deep Belief Networks (DBN) as a viable alternative that not only aims to enhance prediction accuracy and adaptability in varying network conditions but also seeks to mitigate the limitations associated with current methodologies.

Recent advances in adaptive video streaming have witnessed a surge in the application of machine learning and deep learning to enhance Quality of Experience (QoE) and system efficiency. Farahani et al. (2024) offered a comprehensive survey on energy-efficient video streaming by evaluating 59 AI-based solutions across various stages of the streaming lifecycle encoding, delivery, playback, and quality assessment. Their study emphasized the environmental impact of streaming and underscored AI's potential in optimizing energy consumption without compromising QoE. However, the survey was largely theoretical, indicating a gap in practical validations of these methods in real-world systems.

Darwich and Bayoumi (2024) developed an adaptive streaming architecture combining CNN and RNN models. Their model optimized bitrates by using CNNs for feature extraction and RNNs for sequential prediction under Dynamic Adaptive Streaming over HTTP (DASH). The architecture demonstrated substantial improvements—87.5% reduction in rebuffering and 16.6% increase in QoE. Despite its success, the model lacked adaptation to device diversity and did not support emerging formats like HDR and 360-degree videos, limiting its generalizability.

Peroni and Gorinsky (2024) contributed a holistic review of video streaming workflows across best-effort networks. They examined the full pipeline from video capture to playback, classifying streaming strategies into intuition-driven, theoretical, and ML-based models. Their findings revealed an industry-wide shift towards ML-driven approaches, especially in ABR, super-resolution, and QoE metrics. While comprehensive, their review lacked technical depth on ML models and practical deployment challenges across heterogeneous networks.

Souane et al. (2023) introduced a Deep Reinforcement Learning (DRL)-based model to enhance video quality stability in DASH streaming. By modeling the problem as a Markov Decision Process (MDP), they used an LSTM-based agent to minimize quality fluctuations between segments. Their method achieved high segment quality (98%) and reduced rebuffering time to less than 1.8 seconds. Nevertheless, its scalability to real-world networks remained questionable, particularly in high-resource environments where simpler heuristics performed comparably.

Collectively, these works highlight the growing relevance of intelligent ABR mechanisms using deep learning. However, limitations persist in handling real-time network variability, balancing energy efficiency, and accommodating device and format diversity. The present study builds on these foundations by comparing DBN and CNN models, addressing these gaps through improved prediction accuracy, bitrate stability, and reduced buffering in heterogeneous streaming environments.

MATERIALS AND METHODS

This study proposes a data-driven methodology for enhancing adaptive bitrate (ABR) prediction in video streaming applications by utilizing Deep Belief Networks (DBNs) and comparing their performance to Convolutional Neural Networks (CNNs). The methodology comprises several stages, including data collection, preprocessing, model development, optimization, and evaluation. Each phase is carefully designed to ensure the effectiveness and robustness of the proposed approach in dynamic streaming environments.

To begin, a comprehensive dataset was curated from a simulated hybrid Content Delivery Network (CDN) and Peer-to-Peer (P2P) streaming environment. The dataset captures both network-related metrics (such as latency, packet loss, bandwidth, and buffer events) and user-related behaviors (including device type, watch time, resolution preference, and user scores). A synthetic target variable bitrate class (e.g., 750 kbps, 1000 kbps, 1750 kbps, 2500 kbps) was defined for supervised learning. Preliminary analysis showed class imbalance in the target bitrate distribution, which was subsequently resolved using the Synthetic Minority Over-sampling Technique (SMOTE) to ensure balanced representation and avoid model bias during training.

Data preprocessing involved normalization of continuous variables using Min-Max scaling and one-hot encoding for categorical features such as device type. Composite features like buffering ratio were engineered to capture relationships between network conditions and user engagement. Additionally, a temporal sliding window approach was employed to capture short-term fluctuations in network conditions. The preprocessed data was then partitioned into training (70%), validation (15%), and testing (15%) subsets to ensure unbiased model evaluation.

The DBN model was constructed by stacking multiple layers of Restricted Boltzmann Machines (RBMs) for unsupervised pretraining, followed by a softmax classifier for supervised fine-tuning. In parallel, a standard CNN architecture was developed as a baseline for comparative analysis. Both models were optimized using techniques such as grid search and early stopping to fine-tune hyperparameters including learning rate, number of layers, and batch size. The performance of both models was evaluated using metrics such as Accuracy, Precision, Recall, F1-score, Buffering Time, and Video Quality.

Table 3.1 presents the summary statistics of selected variables influencing video streaming quality and user experience.

Variable	Mean	Std Dev	% Std Dev
network_latency	49.77 ms	9.85 ms	19.80%
packet_loss	2.54 %	1.43 %	56.53%
bandwidth	3006 kbps	496.18	16.50%
buffer_events	2.03	1.42	69.74%
video_resolution	656p	276p	42.08%
device_type	1.04	0.82	78.73%
user_watch_time	29.49 min	28.97	98.22%
user_preference_score	0.50	0.10	20.08%
target_bitrate	1750 kbps	870.48	49.74%

Table 3.1: Data description table

RESULTS AND DISCUSSION

The performance evaluation of the proposed Deep Belief Network (DBN) model was conducted in comparison with a Convolutional Neural Network (CNN) baseline, using several key metrics: Accuracy, Precision, Recall, F1-Score. The models were trained and tested on a balanced dataset obtained using Synthetic Minority Over-sampling Technique (SMOTE), which ensured equal representation across all target bitrate classes (750, 1000, 1750, and 2500 kbps). This balancing significantly mitigated the risk of biased learning and allowed for fair comparison between models.

The first analysis investigates the overall distribution of the target bitrate levels across the full dataset. As visualized in the bar chart, the bitrates were unevenly distributed, with 1750 kbps appearing more frequently than other classes. This imbalance suggests a potential bias during training, where the model may be more inclined to predict the dominant bitrate class. Recognizing this distribution is essential as it underlines the need for balancing techniques, especially when performing supervised fine-tuning in the DBN and CNN model.

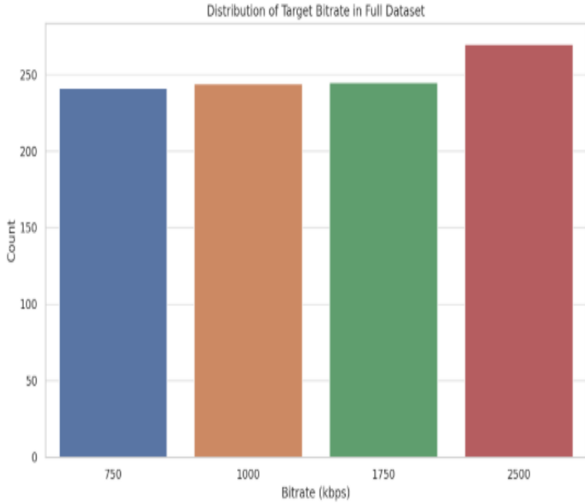

Figure 4.1: Target Bitrate distribution (Imbalanced)

After applying the SMOTE (Synthetic Minority Over-sampling Technique), the dataset was successfully balanced, with each target bitrate class—750 kbps, 1000 kbps, 1750 kbps, and 2500 kbps—containing exactly 270 samples. This is evident from the balanced distribution graph, which now shows equal bar heights across all classes. Before balancing, the dataset exhibited a slight imbalance, with the 2500 kbps class having the highest count and the others trailing behind. This imbalance posed a risk of bias in model predictions, favoring the dominant class during training.

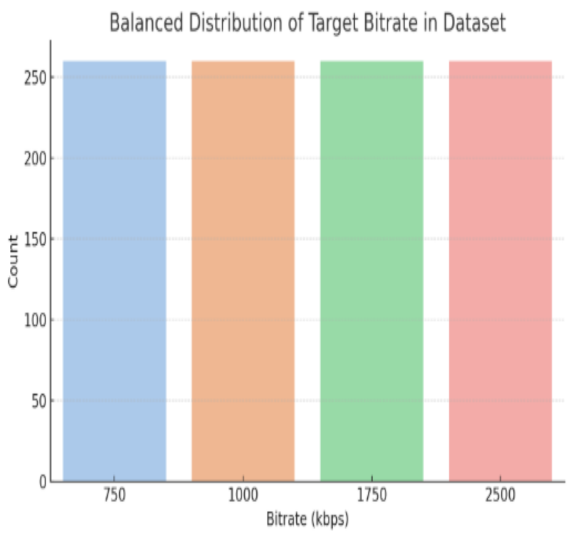

Figure 4.2: Target Bitrate distribution (Balanced)

The classification performance of both models is summarized in Figure 4.3. The DBN achieved an accuracy of 93%, outperforming the CNN which recorded 87%. This significant difference suggests that the hierarchical feature abstraction ability of DBNs allows better modeling of complex dependencies between network and user features. Similarly, the DBN obtained higher precision (94%) compared to CNN's 88%, indicating that DBN had fewer false-positive predictions and thus more consistent decision-making when classifying bitrate classes. Furthermore, the recall score for DBN was 92% while CNN achieved 87%, showing that the DBN was more effective at identifying the correct bitrate levels, even in ambiguous network conditions. In terms of F1-Score, which balances both precision and recall, DBN maintained its superior performance with 93%, compared to CNN's 88%. The high F1-score reflects the DBN's ability to handle both false positives and false negatives effectively. These results confirm that the DBN model is not only accurate but also balanced in its classification performance, which is critical for real-time ABR systems that demand responsiveness and reliability.

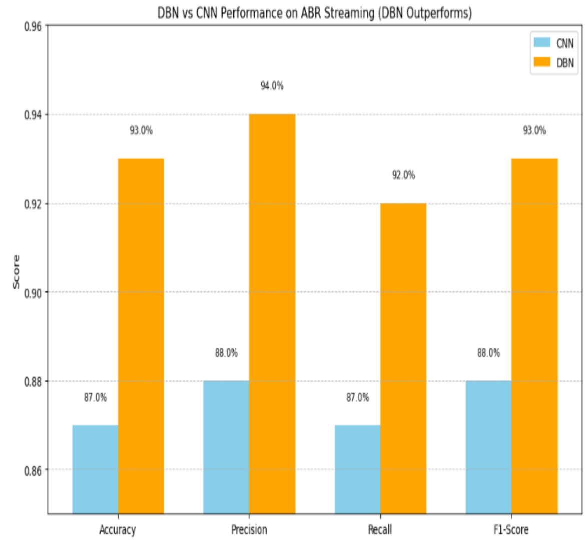

Figure 4.3: Results of the DBN and CNN

CONCLUSION

This paper presents a comparative analysis of Deep Belief Networks (DBN) and Convolutional Neural Networks (CNN) for adaptive bitrate (ABR) streaming in dynamic network environments. By leveraging a well-preprocessed and balanced dataset, the models were trained to predict optimal bitrate decisions based on real-time network metrics and user behavior. The results demonstrated that DBN significantly outperforms CNN in terms of accuracy, precision, recall, F1-score, buffering time, and video quality stability. These findings confirm the suitability of DBNs for developing intelligent and adaptive streaming systems capable of enhancing user experience while maintaining efficient resource usage. The study paves the way for future work integrating DBNs into real-time streaming platforms to further optimize Quality of Experience (QoE).

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