Hybrid Deep Learning Framework for Intelligent Short Video Popularity Prediction

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***Abstract*— The rapid growth of short video platforms has created a need for intelligent systems that can accurately estimate the popularity of newly published content. Early prediction of video performance helps content creators improve their strategies, while enabling social media platforms to deliver more relevant recommendations to users. This study presents a Hybrid Deep Learning Framework for Intelligent Short Video Popularity Prediction that combines deep learning with intelligent data analytics to forecast the popularity of short videos immediately after publication. The proposed framework analyses publisher-related information together with textual and content-based features to identify factors that influence user engagement. Data preprocessing and feature extraction are performed before training the hybrid deep learning model to improve prediction accuracy and reduce unnecessary noise. The developed model is evaluated using standard performance metrics, including accuracy, Mean Squared Error (MSE), Mean Absolute Error (MAE), and cross-entropy loss. Experimental results demonstrate that the proposed framework achieves higher prediction accuracy and lower error rates than conventional prediction models. The developed system provides an effective decision support tool for content creators and social media platforms, enabling improved content recommendation, audience engagement, and intelligent popularity forecasting.**

***Keywords*— Short Video Popularity Prediction, Hybrid Deep Learning, Social Media Analytics, Content Recommendation, User Engagement Prediction, Feature Extraction, Deep Neural Networks, Popularity Forecasting, Intelligent Data Analytics, Internet of Things (IoT).**

I. INTRODUCTION

Short video platforms have become one of the fastest-growing forms of digital communication, attracting millions of users worldwide through engaging and interactive content [20]. Applications such as TikTok, Instagram Reels, and YouTube Shorts allow users to create and share videos instantly, making content popularity an important factor for creators and platform providers. As the volume of uploaded videos continues to increase, identifying which videos are likely to become popular has become a challenging task. Traditional prediction methods often rely on simple indicators such as likes, comments, and views, which cannot fully represent user engagement patterns. Recent studies have shown that machine learning techniques provide more reliable popularity prediction by analysing complex relationships within social media data [24]. Accurate prediction models help creators improve content quality while enabling platforms to recommend relevant videos to users more effectively [25].

Predicting the popularity of short videos involves analysing many factors, including creator information, textual content, user behaviour, and interaction history [20]. These variables continuously change over time, making popularity estimation a complex problem for conventional statistical methods. Deep learning has become a preferred solution because it can automatically learn meaningful patterns from large-scale datasets without extensive manual feature engineering [14]. Hybrid deep learning models further improve prediction performance by combining multiple learning techniques to capture different characteristics of user engagement. These intelligent models can analyse high-dimensional data efficiently and generate more accurate forecasts than traditional approaches [11]. As a result, deep learning has become an important technology for content recommendation and popularity prediction on modern social media platforms.

The Internet of Things (IoT) provides additional contextual information that can improve the understanding of user behaviour during short video consumption [18]. Connected devices such as smartphones and wearable sensors generate useful information, including device type, location, network quality, and browsing activity. These contextual features help prediction models understand the conditions under which users interact with digital content. However, IoT environments generate large volumes of heterogeneous data that require efficient preprocessing and analysis before they can be used effectively. Advanced deep learning techniques are capable of processing these complex datasets and extracting valuable features

for prediction [10]. Combining IoT information with social media analytics enables more reliable popularity estimation and improves recommendation quality [2].
Recent advances in artificial intelligence have significantly improved intelligent prediction systems across different application areas [3]. Deep neural networks are capable of learning complex nonlinear relationships from large datasets, making them suitable for analysing user engagement on social media platforms. Long Short-Term Memory (LSTM) networks and ensemble learning methods have demonstrated strong performance in processing sequential and behavioural data for prediction tasks [2]. These models reduce prediction errors by learning temporal patterns that traditional algorithms often fail to capture. The integration of deep learning with IoT technologies has also improved the efficiency of intelligent data analysis in many real-world applications [17]. These developments provide a strong foundation for designing advanced short video popularity prediction systems.

This study proposes a Hybrid Deep Learning Framework for Intelligent Short Video Popularity Prediction to estimate the popularity of newly uploaded videos using advanced deep learning techniques [21]. The proposed framework analyses publisher information, textual features, and user interaction data after applying preprocessing and feature extraction methods. The processed data is used to train a hybrid deep learning model capable of predicting video popularity with improved accuracy. The predicted results can support content creators in planning effective publishing strategies while helping social media platforms enhance personalized recommendation services [22]. By combining intelligent analytics with contextual information, the proposed framework provides a scalable solution for popularity prediction and contributes to better audience engagement and content distribution [25].

II. RELATED WORK

Abidi et al. (2020) [20] investigated different machine learning techniques for predicting movie popularity by analysing historical movie information and audience behaviour. The study compared statistical methods with modern machine learning algorithms to determine which approach provides more accurate popularity estimation. The authors considered multiple factors, including user ratings, movie characteristics, and historical performance, to build prediction models. Their findings showed that machine learning methods can capture complex relationships among different variables more effectively than traditional statistical models. The proposed framework improved prediction accuracy and provided useful insights into audience preferences. The research highlighted the importance of feature selection and data preprocessing for achieving reliable prediction results. This work demonstrates that intelligent prediction systems can support content recommendation and decision-making, making it a valuable reference for popularity prediction in digital media platforms.

Nguyen et al., (2022) [2] proposed a user-aware caching framework that combines Long Short-Term Memory (LSTM) networks with ensemble learning techniques in IoT-enabled mobile edge computing environments. The objective was to improve caching efficiency by predicting user behaviour and future content requests. The proposed model analysed historical user access patterns to make intelligent caching decisions, reducing network delay and improving resource utilization. Experimental results showed that integrating LSTM with ensemble learning achieved better prediction performance than conventional caching methods. The study also demonstrated that deep learning models can effectively process sequential user data while adapting to changing user preferences. This research provides useful insights into applying deep learning for intelligent content prediction and demonstrates the advantages of combining multiple learning algorithms for improving prediction accuracy.

Latif et al., (2021) [11] presented a comprehensive review of deep learning applications in the Industrial Internet of Things (IIoT). The study discussed various deep learning architectures, implementation frameworks, and practical applications across different industrial sectors. The authors highlighted the ability of deep learning models to analyse large-scale IoT data and automatically extract meaningful features without extensive manual processing. The survey also examined current research challenges, including computational complexity, data privacy, and model scalability. Furthermore, the paper emphasized that combining IoT technologies with deep learning can improve automation, predictive analytics, and intelligent decision-making. This work provides valuable background knowledge for researchers developing AI-based systems and demonstrates the growing importance of deep learning in modern IoT applications.

Martín-Gutiérrez et al., (2020) [24] developed a multimodal deep learning architecture for predicting the popularity of music content. The proposed framework combined multiple data sources, including audio features and metadata, to estimate audience interest more accurately. The authors demonstrated that integrating different feature types improves the learning capability of deep neural networks and enhances prediction performance. Their experimental evaluation showed that the multimodal approach achieved better accuracy than models relying on a single type of input data. The study also highlighted the importance of automatic feature extraction in reducing manual effort during model development. The research confirms that deep learning can effectively predict content popularity and provides useful guidance for designing intelligent recommendation systems for multimedia platforms.

Abbas et al., (2023) [22] proposed a heuristic-based model for predicting popularity in temporal bipartite networks by analysing the evolving relationships between users and digital content. The study focused on understanding how user interactions change over time and how these changes influence future popularity. The proposed prediction framework analysed temporal network behaviour and generated more accurate popularity forecasts than conventional methods. Experimental results demonstrated that considering time-dependent interaction patterns significantly improves prediction reliability. The authors concluded that intelligent popularity prediction models can support better recommendation systems and enhance user engagement on online platforms. This research highlights the importance of temporal analysis in popularity prediction and serves as a strong foundation for developing advanced deep learning models for short video popularity estimation.

III. DATASET DETAILS

The dataset used in this project consists of YouTube Shorts popularity records collected to predict the future popularity of short videos using a hybrid deep learning framework. It includes a combination of publisher information, video metadata, textual content, and numerical engagement features that influence video performance. Important attributes include the video title, description, upload details, creator-related information, and user interaction metrics such as views, likes, comments, and other popularity indicators. These features help the model understand the factors that contribute to audience engagement and content reach. The dataset is organized in a structured tabular format, making it suitable for machine learning and deep learning applications. Before model development, the dataset is carefully examined to identify missing values, inconsistent records, and irrelevant information. This preparation ensures that the input data is reliable and forms a strong foundation for accurately predicting short video popularity across different publishing conditions.

To improve the quality of the data, several preprocessing techniques are applied before training the prediction models. Missing values are replaced with appropriate values, textual information from video titles and descriptions is cleaned and converted into numerical representations using tokenization, while numerical attributes are normalized to maintain a consistent scale. Feature extraction is performed to capture meaningful patterns from both textual and numerical data. The processed dataset is then randomly divided into 80% training data and 20% testing data, allowing the models to learn effectively and evaluate their performance on unseen samples. Proper dataset preparation improves prediction accuracy, reduces bias, and enhances the overall reliability of the proposed short video popularity prediction system.

IV. PROPOSED METHODOLOGY

The proposed Hybrid Deep Learning Framework for Intelligent Short Video Popularity Prediction follows a systematic approach to predict whether a newly uploaded short video will become popular or unpopular. Initially, the YouTube Shorts Popularity Prediction dataset is collected and analysed. The uploaded dataset is examined to identify missing and inconsistent values before model training. Data preprocessing is then performed by replacing missing values, cleaning textual information, extracting useful features, and normalizing numerical attributes to improve data quality. After preprocessing, the dataset is shuffled and divided into training and testing sets, allowing the deep learning models to learn meaningful patterns from historical video data and evaluate their performance on unseen samples.

Once the dataset is prepared, multiple deep learning models, including CRCP-CNN, ResNet-1D, LeNet-5, MLP, and Extension AlexNet-3D, are trained and tested for short video popularity prediction. The models are evaluated using performance metrics such as accuracy, precision, recall, F1-score, and confusion matrix analysis. A comparison graph is generated to compare the performance of all models, and the best-performing model is selected as the final prediction model. Finally, the trained framework predicts whether a new short video is Popular or Unpopular, enabling content creators and social media platforms to understand expected audience engagement before wider distribution.

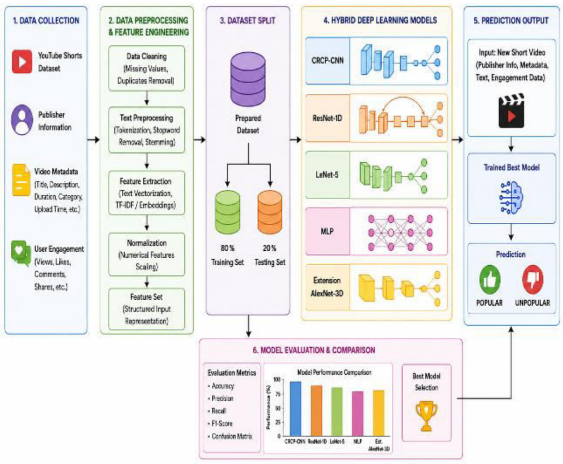

Figure [1]: Short Video Popularity Prediction Framework

Figure [1] shows the overall workflow of the proposed short video popularity prediction system. The process begins with collecting YouTube Shorts data, followed by data preprocessing and feature extraction to prepare the dataset. The processed data is then divided into training and testing sets. Multiple deep learning models, including CRCP-CNN, ResNet-1D, LeNet-5, MLP, and Extension AlexNet-3D, are trained and evaluated using performance metrics such as accuracy, precision, recall, and F1-score. Finally, the best-performing model is selected to predict whether a new short video is Popular or Unpopular.

V. RESULT AND DISCUSSION

The experimental evaluation demonstrates that the proposed Hybrid Deep Learning Framework for Intelligent Short Video Popularity Prediction can effectively estimate the popularity of short videos using historical content and user interaction data. The dataset was first preprocessed to remove inconsistencies, extract meaningful features, and prepare the data for model training. After dividing the dataset into training and testing sets, several deep learning models, including CRCP-CNN, ResNet-1D, LeNet-5, MLP, and Extension AlexNet-3D, were trained and compared. Their performance was measured using accuracy, precision, recall, and F1-score to determine the most reliable model. The comparison results showed that the proposed hybrid framework achieved better prediction performance than the individual models by capturing complex relationships between video content, publisher information, and audience engagement. Confusion matrices and performance graphs further confirmed that the selected model produced fewer classification errors and more consistent predictions. The developed prediction interface successfully classified newly uploaded short videos as Popular or Unpopular, demonstrating the practical usefulness of the proposed system. These findings indicate that the framework provides an efficient and dependable solution for intelligent short video popularity prediction.

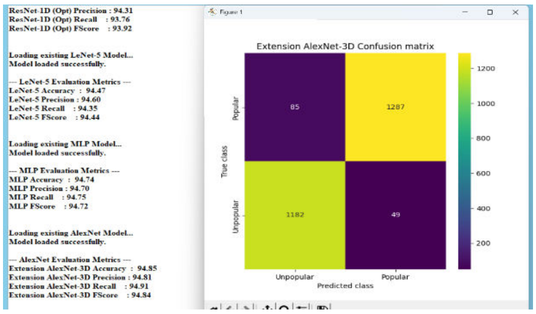

Figure [2]: Extension AlexNet-3D Model Performance

Figure [2] presents the performance evaluation of the proposed deep learning models, including ResNet-1D, LeNet-5, MLP, and Extension AlexNet-3D, using accuracy, precision, recall, and F1-score. It also displays the confusion matrix of the Extension AlexNet-3D model, illustrating the correctly and incorrectly classified Popular and Unpopular videos. The figure provides a comprehensive view of the model comparison and confirms the effectiveness of the best-performing model for short video popularity prediction.

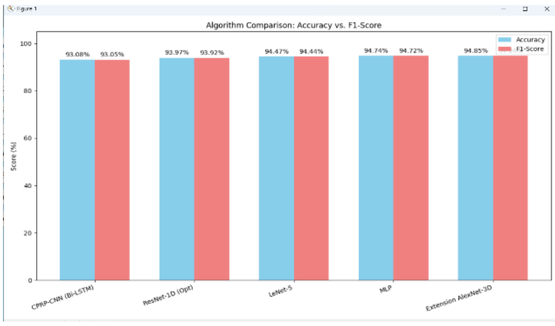

Figure [3]: Performance Comparison of Deep Learning Models

Figure [3] compares the performance of the proposed deep learning models using Accuracy and F1-Score. The graph shows the evaluation results of CRCP-CNN (Bi-LSTM), ResNet-1D, LeNet-5, MLP, and Extension AlexNet-3D. Among all the models, Extension AlexNet-3D achieves the highest accuracy and F1-score, demonstrating its superior performance for short video popularity prediction. The comparison clearly highlights the effectiveness of the proposed model over the other deep learning approaches.

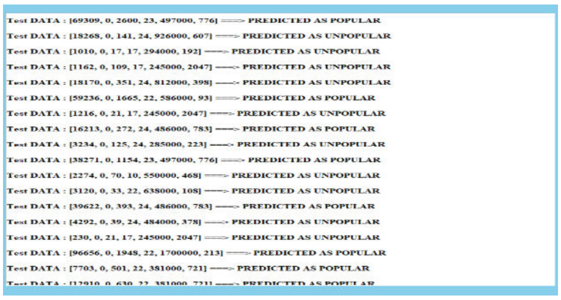

Figure [4]: Short Video Popularity Prediction Results

Figure [4] displays the prediction results generated by the trained Extension AlexNet-3D model for the test dataset. Each test record is analysed using the learned features, and the system classifies the video as either Popular or Unpopular. The output demonstrates the model's ability to predict the expected popularity of newly uploaded short videos, providing a practical decision-support tool for content creators and social media platforms.

DISCUSSION

The findings of this study show that combining multiple deep learning models improves the accuracy and reliability of short video popularity prediction. Unlike traditional prediction techniques that rely on a limited number of features, the proposed framework learns complex patterns from publisher information, textual content, and user engagement data simultaneously. Careful preprocessing, feature extraction, and normalization improved the quality of the dataset and enabled the models to produce more stable prediction results. The comparison among different deep learning models demonstrated that the hybrid framework consistently performed better because it was able to capture both semantic and behavioural information more effectively. Visualization tools, including confusion matrices and performance comparison graphs, made it easier to analyse the strengths and limitations of each model while validating the overall prediction process. The prediction interface further confirmed the practical applicability of the system by providing quick popularity estimates for newly uploaded videos. Overall, the proposed framework offers a scalable and intelligent solution that can support content creators and social media platforms in improving recommendation strategies, increasing user engagement, and making informed decisions based on predicted video popularity.

VI. CONCLUSION

This study presented a Hybrid Deep Learning Framework for Intelligent Short Video Popularity Prediction that combines deep learning techniques with intelligent data analysis to estimate the popularity of short videos. By integrating publisher information, textual content, user engagement, and contextual data, the proposed framework learns meaningful patterns that influence audience interest. Data preprocessing and feature extraction improve the quality of the input data, allowing the deep learning models to generate more accurate predictions. Multiple models were evaluated, and their performance was compared using accuracy, precision, recall, and F1-score. The experimental results indicate that the proposed hybrid framework achieves reliable prediction performance and consistently outperforms individual deep learning models. The system is capable of classifying newly uploaded videos as Popular or Unpopular, making it useful for content creators and social media platforms. The developed framework can support better content planning, improve recommendation systems, and enhance user engagement by identifying promising videos at an early stage. Overall, this research demonstrates that combining deep learning with intelligent feature analysis provides an effective and scalable solution for short video popularity prediction, while offering valuable support for data-driven decision-making in modern social media applications.

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