Published by :
https://www.ijert.org/
An International Peer-Reviewed Journal

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 10, NCREHAASTE - 2026

A Systematic Review of Predictive Modeling Techniques in Social Media Video Analytics (September 2026)

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***Abstract*—**Social media platforms have transformed how people create, consume, and share digital content. Platforms such as YouTube, Instagram, TikTok, and Twitter generate vast amounts of multimedia data, creating valuable opportunities for predictive analytics. Predictive modeling can help identify videos with high trending potential, enabling content creators, marketers, educators, and platform developers to optimize content strategies and improve user engagement.

This systematic literature review examines the evolution of predictive modeling techniques for social media video analytics, with particular emphasis on trending-video prediction. It traces the progression from traditional machine learning algorithms to deep learning and multimodal frameworks and analyzes the datasets, feature-engineering strategies, evaluation metrics, and application domains used in previous studies.

A systematic review methodology was adopted to identify relevant studies from major scientific databases, including Scopus, Web of Science, and IEEE Xplore. The selected publications were critically analyzed according to predictive techniques, datasets, feature representations, performance metrics, and application areas, including view-count prediction, engagement forecasting, video popularity prediction, and recommendation systems.

The analysis indicates that deep learning models, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), are effective at learning complex spatial and temporal patterns from video data. Hybrid and multimodal frameworks that integrate visual, textual, audio, and metadata features generally achieve better predictive performance than single-modal approaches. However, challenges remain in data heterogeneity, scalability, limited benchmark datasets, model interpretability, and the rapidly changing nature of social media platforms.

Overall, this review summarizes current predictive modeling approaches, identifies major research trends and limitations, and highlights promising directions for developing accurate, robust, scalable, and explainable models for social media video analytics.

***Index Terms*— Social Media Video Analytics; Predictive Modeling; Machine Learning; Deep Learning; Video Content Analysis; Engagement Prediction; Multimodal Learning; Systematic Literature Review; Video Popularity Prediction; Trend Prediction.**

I. Introduction

Social media platforms have become major digital environments for creating, sharing, and consuming multimedia content. Platforms such as YouTube, Instagram, TikTok, and Twitter enable billions of users to upload, view, and interact with videos, generating enormous volumes of user-generated content. Among the features offered by these platforms, trending sections play an important role in promoting videos that rapidly gain popularity and attract audience attention.

The selection of trending videos is influenced by multiple engagement indicators, including views, likes, comments, shares, watch time, audience retention, and user-interaction patterns. Videos that become trending receive greater visibility, which can increase audience engagement, subscriber growth, and content reach. Consequently, predicting whether a video is likely to trend has become an important research problem for content creators, digital marketers, educators, and platform developers.

Predictive modeling techniques can forecast video popularity by analyzing historical engagement data, content characteristics, creator information, and user behavior. Reliable predictions can help creators optimize content strategies, marketers identify promising promotional opportunities, and educators design videos that encourage learner engagement and accessibility.

Early research on social media trend prediction primarily relied on statistical methods and conventional machine learning algorithms. These approaches focused on metadata features such as follower counts, views, likes, comments,

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shares, and upload time. Previous studies used methods including Linear Regression, Support Vector Machines (SVM), Decision Trees, Random Forests, and K-Nearest Neighbors (KNN) to predict content popularity from handcrafted interaction and metadata features.

With advances in artificial intelligence, predictive modeling has progressed toward sophisticated deep learning architectures. Recent studies have shown that Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and hybrid multimodal frameworks can learn complex visual, textual, temporal, and contextual representations from social media data. These approaches improve prediction by combining multiple information sources rather than relying only on engagement statistics.

Despite these advances, several challenges remain. Social media data are dynamic, heterogeneous, and continuously evolving, which makes it difficult to develop models that generalize across platforms. The lack of standardized benchmark datasets, platform-specific algorithms, class imbalance, scalability constraints, and limited model interpretability further restrict the practical deployment of predictive systems.

This systematic literature review analyzes predictive modeling techniques used in social media video analytics. It compares traditional machine learning, deep learning, and hybrid approaches; examines commonly used datasets, feature-engineering strategies, and evaluation metrics; and identifies research gaps, current challenges, and future directions for developing more accurate, scalable, and explainable predictive models.

II. LITERATURE REVIEW

The rapid growth of social media has generated substantial research interest in predicting video popularity and user engagement. Over the past decade, researchers have explored traditional machine learning, deep learning, sentiment analysis, and multimodal learning approaches. This section critically reviews the literature on predictive modeling for social media video analytics.

Several studies have examined sentiment analysis as a means of understanding user opinions and predicting video popularity. Han and Kim [1] showed that morphological sentence-pattern models can analyze sentiments expressed in social media comments, suggesting that sentiment information can help characterize audience perception and engagement with online video content.

Chen [2] investigated personal branding on YouTube and its relationship with user engagement and video popularity. The study reported that creator reputation, content quality, and audience interaction influence video performance and long-term channel growth.

Similarly, Li [3] and Mohana Prabha et al. [6] examined factors affecting online video popularity. Their studies used sentiment-analysis techniques to evaluate user comments and feedback, indicating that audience sentiment may serve as a predictor of future popularity.

Soleymani et al. [7] introduced a multimodal sentiment-analysis framework integrating textual, visual, and audio information to improve sentiment classification. Their work demonstrated the value of multimodal learning for capturing complementary information from multiple sources and supporting applications such as video recommendation, personalized advertising, and user-behavior analysis.

Rangaswamy et al. [8] proposed a framework for extracting metadata from YouTube videos using sentiment-analysis techniques. The approach automatically generated metadata and classified videos into appropriate categories based on audience sentiment, with potential benefits for video organization and retrieval.

Mulholland et al. [9] analyzed emotional sentiment in YouTube comments using machine learning. Their findings suggested that emotional reactions influence user engagement and can provide useful signals for predicting audience interaction with video content.

Chelaru et al. [10] investigated the integration of social feedback into video-ranking systems. By incorporating engagement indicators such as likes, comments, and shares, their approach improved the prediction of video popularity and recommendation performance.

Overall, early predictive models relied heavily on engagement-based features such as views, likes, comments, shares, and subscriber counts. Although these variables remain useful indicators of popularity, they provide limited information about the semantic and contextual characteristics of video content.

Recent research has therefore moved toward deep learning and hybrid models that combine visual, textual, temporal, and metadata features. These approaches can exploit complementary information from multiple sources and generally provide stronger predictive performance and better generalization than conventional machine learning methods.

Nevertheless, important challenges persist. Many studies use platform-specific datasets, limiting cross-platform generalizability. In addition, heterogeneous feature representations, rapidly changing platform algorithms, scalability constraints, limited benchmark datasets, and insufficient interpretability remain barriers to practical deployment.

III. RESEARCH GAP

The reviewed literature reveals several important research gaps:

Most studies rely heavily on engagement metrics such as views, likes, and comments, while giving comparatively limited attention to temporal patterns and multimodal feature fusion.

Relatively few studies integrate visual, textual, audio, and metadata features within a unified predictive framework.

The absence of standardized benchmark datasets makes fair

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and reproducible comparisons between predictive models difficult.

Many studies evaluate models on a single social media platform, which limits the generalizability of their findings.

Model interpretability and explainability remain underexplored despite their importance in real-world applications.

Emerging approaches, including Transformer-based architectures and foundation models, have not yet been widely explored for social media trend prediction.

Table 1. Comparative Analysis of Existing Predictive Modeling Techniques for Social Media Video Analytics

Ref.	Authors	Year	Algorithm(s)	Research Focus	Reported Performance	Strengths	Limitations
1	S. O. Olukumoro et al.	2022	KNN, Random Forest, Grid Search	YouTube videos using video tags	KNN (81.7 %), R.F. (86.5 %), G.S.(78.6%)	Compared multiple machine learning algorithms	Not consider multimodal information.
2	H. M. Caldera et al.	2021	D.T, R.F, N.B, SVM	YouTube trending videos	DT (84.1 %), RF (85.6 %), NB (82.7 %), SVM (83.6 %)	classical machine learning classifiers.	Not include deep learning models.
3	Arushi Pathik et al.	2022	Linear Regression, Decision Tree, Random Forest	YouTube trend analysis	LR (82.0 %), DT (88.8 %), RF (82.7 %)	Demonstrates the effectiveness of Decision Trees for trend prediction.	Does not incorporate temporal
4	Farzana Shaikh et al.	2018	Hive, Apache Mahout, HDFS, MapReduce	Large-scale YouTube data analysis using Hadoop	82.5–86.8%	Suitable for processing large-scale distributed datasets.	Advanced predictive modeling.
5	R. Sangeetha & R. Vidhya	2022	SVM, Linear Regression, Gradient Boosting, KNN	Prediction of YouTube view count	SVM (86.4 %), LR (81.3 %), GB (79.7 %), KNN (86.9 %)	Compares multiple supervised learning algorithms	Evaluation is limited to engagement-based features.
6	Nafis Irtiza Tripto et al.	2018	SVM	Multilabel video classification	83.0%	Demonstrates the applicability of SVM	does not compare it with modern deep learning approaches.

IV. Traditional Machine Learning

Traditional Machine Learning (ML) techniques employ statistical and computational algorithms to identify patterns and relationships within data using predefined or engineered features. Common approaches include Support Vector Machine (SVM), Decision Tree, K-Nearest Neighbors (KNN), Random Forest, and Linear Regression. These techniques are widely used for classification, regression, and prediction tasks. For example, Support Vector Machines are designed to construct effective decision boundaries for classification problems [1], while Random Forests combine multiple decision trees to improve predictive performance and robustness [2]. In the context of social media video analysis, traditional ML methods can be applied to structured metadata and extracted content features for predicting video popularity and trending behavior.

V. Deep Learning

Deep Learning is a subfield of machine learning that utilizes multi-layer neural networks to automatically learn hierarchical and complex representations from data [3]. Convolutional Neural Networks (CNNs) are particularly effective for extracting visual representations from images and video frames, whereas Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are suitable for modeling sequential and temporal information. LSTM networks were specifically developed to address challenges associated with learning long-term dependencies in sequential data [4]. Therefore, deep learning techniques are suitable for analyzing the complex visual, textual, and temporal characteristics of social media videos.

VI. Multimodal/Hybrid Approach

A Multimodal or Hybrid approach integrates information from multiple data modalities to obtain a more comprehensive representation of the target content. Multimodal machine learning focuses on models capable of processing and relating information from different modalities, with important challenges including representation, alignment, and fusion [5].

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In social media video analysis, a multimodal/hybrid approach can combine visual, textual, audio, temporal, and metadata features, such as views, likes, comments, shares, upload time, and engagement-related attributes. The integration of these complementary sources of information can enable the model to capture relationships that may not be adequately represented by a single modality.

VII. Methodology

Do The methodology adopted in this study follows a systematic and structured approach for analyzing existing research on social media video analysis and identifying suitable predictive techniques for trending-video prediction. The overall research process consists of literature collection, study selection, dataset and feature analysis, model categorization, performance comparison, research gap identification, and identification of future research directions.

A. Literature Collection

A systematic literature collection process was conducted to identify relevant studies related to social media video analysis, video popularity prediction, trending-content detection, machine learning, deep learning, and multimodal learning. Relevant research articles were collected from established academic databases and digital libraries using combinations of keywords such as social media video analysis, trending video prediction, video popularity prediction, social media analytics, machine learning, deep learning, multimodal learning, and content prediction. The collected literature was reviewed to understand the existing methodologies, datasets, features, algorithms, and evaluation strategies used in previous studies.

B. Study Selection

The identified studies were screened based on their relevance to the research objectives. Studies directly related to social media content analysis, video popularity or trend prediction, machine learning, deep learning, and multimodal approaches were considered for further analysis. Studies with insufficient methodological information, limited relevance to video-based social media analysis, or inadequate experimental evaluation were excluded. The final selection was used to establish a focused understanding of existing research and methodological developments in this domain.

C. Dataset and Feature Analysis

The selected studies were analyzed with respect to the datasets and features employed for prediction and analysis. Particular attention was given to metadata features, textual features, visual features, audio features, temporal features, and user-engagement features. Metadata may include attributes such as views, likes, comments, shares, upload time, and other engagement indicators. Textual information can be obtained from titles, descriptions, hashtags, and comments, while visual and audio features can be extracted from video content. Temporal features are considered to capture changes in engagement and popularity over time. This analysis helps determine the contribution of different feature types to social media trend prediction.

D. Model Categorization

The existing approaches were categorized into three major groups: Traditional Machine Learning, Deep Learning, and Multimodal/Hybrid Approaches. Traditional machine learning models include Support Vector Machine (SVM), Decision Tree, K-Nearest Neighbors (KNN), Random Forest, and Linear Regression. Deep learning approaches include Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks. Multimodal or hybrid approaches integrate multiple information sources, such as visual, textual, audio, temporal, and metadata features, to provide a more comprehensive representation of social media videos.

E. Performance Comparison

The performance of the identified approaches was compared based on the evaluation measures reported in the selected studies. Depending on the prediction task, commonly used measures include Accuracy, Precision, Recall, F1-score, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Area Under the ROC Curve (AUC). The comparison was performed to examine the relative effectiveness of different model categories and to identify the conditions under which particular approaches demonstrate better predictive performance.

F. Research Gap Identification

Based on the comparative analysis, existing limitations and research gaps were identified. The analysis indicates that several existing approaches focus primarily on individual modalities or limited feature sets, while the combined utilization of visual, textual, audio, temporal, and metadata information remains comparatively challenging. In addition, early prediction of trending videos requires the effective modeling of temporal engagement patterns and the integration of heterogeneous features. These observations highlight the need for more comprehensive and robust predictive frameworks capable of integrating multiple information sources for early identification of trending social media videos.

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G. Future Research Directions

Based on the identified research gaps, future research should focus on developing multimodal and hybrid predictive frameworks that effectively integrate heterogeneous social media data. Future studies may investigate the combination of CNN-based visual feature extraction, NLP-based textual analysis, LSTM or other temporal models, and traditional machine learning algorithms for improved prediction. Attention mechanisms, feature-level or decision-level fusion, explainable artificial intelligence, and real-time trend prediction can also be explored to enhance model effectiveness, interpretability, and practical applicability.

H. Overall Methodological Framework

The methodology therefore provides a systematic pathway from literature collection to research-gap identification and future model development. This framework enables the study to critically evaluate existing approaches and provides a foundation for designing a predictive model for social media trending-video analysis and early trend prediction.

VIII. RESULTS

The comparative analysis shows that Random Forest, Decision Tree, and Support Vector Machine (SVM) are among the most frequently used traditional machine learning algorithms for predicting video popularity. Across the reviewed studies, these methods generally achieve accuracies of approximately 82%–89%, indicating their effectiveness for structured engagement data.

However, classical machine learning models typically depend on manually engineered features such as views, likes, comments, tags, and other metadata. Consequently, they have limited ability to capture the complex visual, textual, and temporal relationships present in multimedia content.

Recent studies increasingly emphasize deep learning and multimodal techniques because these models can learn hierarchical representations from multiple data sources. Such approaches offer greater predictive capability and improved generalization, although computational complexity, limited benchmark datasets, scalability, and interpretability remain significant challenges.

Overall, the literature supports further development of hybrid multimodal frameworks that integrate visual, textual, temporal, and metadata features to improve the accuracy, robustness, and scalability of social media video popularity prediction.

Figure 1 illustrates the comparative performance of the predictive modeling techniques reported in the reviewed studies. The results indicate that traditional machine learning approaches, including KNN, Random Forest, Decision Tree, SVM, and Linear Regression, generally achieve predictive performance in the range of approximately 82%–89%. Random Forest and Decision Tree demonstrate comparatively strong performance across the reviewed studies

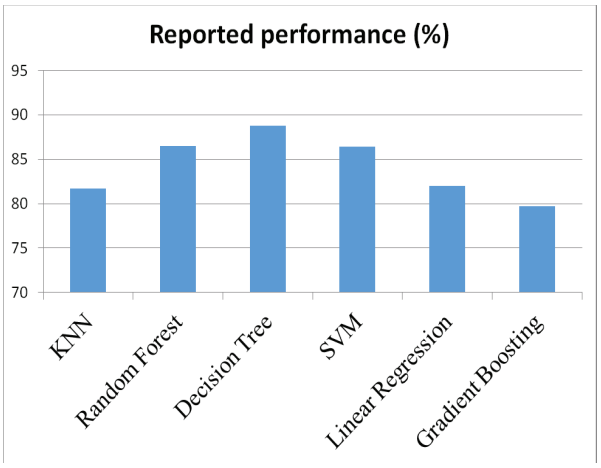


Figure 1

IX. CONCLUSION

This systematic literature review examined predictive modeling techniques for social media video analytics, with particular emphasis on trending and popular video prediction. The reviewed studies show a progression from conventional machine learning methods toward deep learning and multimodal frameworks. Traditional approaches, including SVM, Decision Tree, KNN, Random Forest, and Linear Regression, can predict popularity effectively when based on structured engagement features such as views, likes, comments, and shares.

Deep learning approaches extend these capabilities by learning complex representations from visual, textual, temporal, and metadata features. Hybrid and multimodal models can combine complementary information from multiple sources and therefore provide stronger predictive performance and robustness than many single-modal or conventional approaches.

Despite this progress, important limitations remain. Platform-specific datasets reduce cross-platform generalizability, while heterogeneous data sources, a lack of standardized benchmarks, limited interpretability, scalability constraints, and rapidly changing platform algorithms hinder practical deployment.

Future research should therefore investigate scalable, explainable, and multimodal predictive frameworks that integrate visual, textual, audio, temporal, and metadata features within a unified architecture. Transformer-based models, Explainable Artificial Intelligence (XAI), Graph Neural Networks (GNNs), and Large Language Models (LLMs) also offer promising directions for improving predictive performance and interpretability.

In summary, the reviewed literature establishes the current state of predictive modeling for social media video analytics and highlights the need for robust, interpretable, and cross-platform approaches. These findings can guide the development of more accurate and efficient systems for video popularity and trend prediction.

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ACKNOWLEDGMENT

The authors would like to express their sincere gratitude to IFTM University, Lodhipur Rajput, Moradabad, Uttar Pradesh, India, for providing the academic environment and institutional support associated with this research work. The authors also acknowledge the academic context of the Department of Computer Science and Application, which supported the development and completion of this systematic review on predictive modeling techniques in social media video analytics.

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