

## A SHORT VIDEO POPULARITY PREDICTION USING IOT AND DEEP LEARNING

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### ABSTRACT

The rapid growth of social media platforms and short-video applications has significantly increased the demand for intelligent systems that can predict video popularity in advance. Understanding the factors that influence video engagement, such as views, likes, shares, and comments, is essential for content creators, marketers, and platform providers. This project, “Short Video Popularity Prediction Using IoT and Deep Learning,” proposes an advanced framework that leverages Internet of Things (IoT) data and Deep Learning techniques to accurately predict the popularity of short videos before or shortly after publication. The proposed system integrates data collected from IoT-enabled devices such as smartphones, wearables, and user interaction sensors, which capture contextual information including user behavior, location, device usage patterns, and real-time engagement metrics. This data is combined with video-specific features such as duration, content type, visual quality, hashtags, and posting time. The system utilizes deep learning models such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) to extract spatial and temporal features from video content and user interaction sequences. These models are capable of learning complex nonlinear relationships between input features and popularity outcomes. Additionally, attention mechanisms may be incorporated to improve prediction accuracy by focusing on the most relevant features. The system is evaluated using performance metrics such as accuracy, mean squared error (MSE), and F1-score. The results demonstrate that integrating IoT data with deep learning significantly improves prediction accuracy compared to traditional approaches. The proposed framework enables content creators to optimize their videos for maximum reach and engagement, while platforms can enhance recommendation systems. This research contributes to the fields of social media analytics, IoT-based data intelligence, and deep learning, providing a scalable and efficient solution for predicting short video popularity.

**Keywords** : Short Video Popularity, Deep Learning, Internet of Things, CNN, RNN, Social Media Analytics, Predictive Modeling, User Behavior Analysis, Big Data, Content Recommendation

### I.INTRODUCTION

The rapid growth of social media platforms such as TikTok, Instagram Reels, and YouTube Shorts has led to an exponential increase in short video content consumption. Predicting the popularity of such videos has become a critical task for content creators, marketers, and platform providers. Popularity is typically measured using metrics such as views, likes, shares, and comments, which reflect user engagement and content reach. However, accurately predicting these metrics is challenging due to the dynamic and complex nature of user behavior. Traditional statistical and machine learning methods often fail to capture nonlinear relationships and temporal dependencies in user interactions. With the advancement of Artificial Intelligence (AI) and Deep Learning, new opportunities have emerged to analyze large-scale data and generate accurate predictions. These technologies enable systems to learn patterns from historical data and make intelligent decisions. Additionally, the integration of contextual information such as posting time, content type, and audience demographics further enhances prediction accuracy. The increasing availability of big data has made it possible to develop advanced models that can process and analyze complex datasets efficiently. This has led to the development of intelligent systems capable of predicting video popularity with high accuracy.

Recent advancements in the Internet of Things (IoT) have further improved the capability of data-driven systems by enabling real-time data collection from connected devices. IoT devices such as smartphones, wearable devices, and sensors capture valuable contextual information including user behavior, location, device usage, and interaction patterns. This data provides deeper insights into user preferences and content consumption habits. By integrating IoT data with deep learning models, it becomes possible to develop more accurate and personalized prediction systems. Deep learning models such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are widely used to analyze visual and temporal features of video content. CNNs are effective in extracting spatial features from video frames, while RNNs and LSTM networks capture sequential patterns in user interactions. These models can learn complex relationships between input features and popularity outcomes. Furthermore, attention mechanisms can be used to focus on the most relevant features, improving prediction

performance. Despite these advancements, challenges such as data privacy, scalability, and computational complexity remain significant concerns.

The proposed system, Short Video Popularity Prediction Using IoT and Deep Learning, aims to address these challenges by integrating multiple data sources and advanced learning techniques. The system collects data from IoT devices and social media platforms, preprocesses the data, and applies deep learning models to predict video popularity. It considers multiple factors such as content features, user engagement, and contextual information to generate accurate predictions. The system also includes visualization tools to present insights in an understandable format. By leveraging AI and IoT technologies, the system provides valuable recommendations to content creators, helping them optimize their content for maximum reach and engagement. Additionally, platform providers can use the system to improve recommendation algorithms and enhance user experience. The proposed approach contributes to the fields of social media analytics, big data processing, and intelligent systems, offering a scalable and efficient solution for predicting short video popularity in modern digital environments.

## II SURVEY OF RESEARCH

The work proposed by H. Pinto, J. Almeida, and M. Gonçalves (2013) [1] focuses on predicting the popularity of online content using early user engagement metrics. Their study analyzed features such as initial views, likes, and shares to estimate future popularity. The methodology involved statistical modeling and regression techniques applied to social media datasets. The results demonstrated that early engagement signals are strong indicators of long-term popularity. The authors emphasized the importance of temporal features in predicting content performance. However, the approach was limited in handling complex nonlinear relationships present in large-scale datasets. Despite this limitation, the research laid a strong foundation for popularity prediction systems. In addition to early engagement features, the study also explored the impact of content characteristics such as video length and metadata on popularity prediction [1]. The authors found that combining multiple features improves prediction accuracy compared to using a single feature. The model was trained using historical data and evaluated on unseen datasets to ensure generalization. The results showed moderate prediction accuracy, indicating the need for more advanced techniques. The authors suggested that incorporating user behavior data could further enhance model performance. Furthermore, the study highlighted the limitations of traditional machine learning approaches in capturing dynamic user interactions [1]. The lack of real-time data processing reduced the system's effectiveness in rapidly changing environments. The authors recommended the use of advanced models capable of handling sequential and contextual data. This research provided valuable insights into feature selection and data analysis for popularity prediction systems.

The approach proposed by Y. Zhou, T. Liu, and D. Wang (2016) [2] explores the use of deep learning techniques for predicting social media popularity. Their study utilized Recurrent Neural Networks (RNNs) to capture temporal patterns in user engagement data. The methodology involved training RNN models on sequential data such as time-series views and interactions. The results demonstrated that deep learning models outperform traditional regression techniques in capturing temporal dependencies. The authors emphasized the importance of sequential modeling in understanding user behavior. The research also incorporated multiple input features such as user profiles, posting time, and content metadata to improve prediction accuracy [2]. The integration of heterogeneous data sources allowed the model to learn complex relationships between different variables. The results showed a significant improvement in prediction performance compared to baseline models. The authors highlighted that deep learning models can adapt to evolving user behavior patterns. However, the study faced challenges related to computational complexity and the need for large training datasets [2]. Training deep learning models required significant computational resources and time. The authors suggested optimizing model architectures and using efficient training techniques. Despite these challenges, the research contributed significantly to the advancement of deep learning-based popularity prediction systems.

The work proposed by S. Hochreiter and J. Schmidhuber (1997) [3] introduces Long Short-Term Memory (LSTM) networks for modeling sequential data. Although originally developed for general sequence prediction tasks, LSTM networks have been widely applied in popularity prediction systems. The methodology involves capturing long-term dependencies in time-series data, which is essential for analyzing user engagement patterns over time. The results demonstrated that LSTM models effectively handle vanishing gradient problems and improve prediction accuracy. In the context of video popularity prediction, LSTM networks are used to analyze sequences of user interactions such as views, likes, and comments [3]. The model learns temporal patterns and predicts future popularity based on historical trends. The authors emphasized the importance of memory cells in retaining relevant information over long sequences. This capability makes LSTM suitable for modeling dynamic user behavior in social media platforms. Despite its advantages, the LSTM model requires careful tuning of parameters and large

datasets for optimal performance [3]. The computational cost is also higher compared to traditional models. The authors suggested combining LSTM with other deep learning techniques for improved results. This research played a crucial role in enabling temporal modeling in popularity prediction systems.

The approach proposed by A. Krizhevsky, I. Sutskever, and G. Hinton (2012) [4] focuses on Convolutional Neural Networks (CNNs) for image and video feature extraction. Their study demonstrated that CNNs can effectively learn spatial features from visual data. The methodology involved training deep CNN architectures on large-scale datasets to extract meaningful patterns. The results showed significant improvements in classification and feature extraction tasks. In video popularity prediction, CNNs are used to analyze visual content such as frames, thumbnails, and scene composition [4]. The extracted features are combined with user interaction data to improve prediction accuracy. The authors highlighted the importance of hierarchical feature extraction in understanding visual content. CNNs can identify patterns such as color distribution, object presence, and visual quality, which influence video popularity. However, CNN-based models require large labeled datasets and high computational power for training [4]. The authors suggested using transfer learning techniques to reduce training time and improve performance. Despite these challenges, the research significantly contributed to the development of deep learning-based video analysis systems.

The work proposed by J. Gubbi et al. (2013) [5] explores the role of the Internet of Things (IoT) in data-driven systems. Their study introduced a framework for collecting real-time data from connected devices. The methodology involved integrating sensors, communication networks, and cloud computing for data processing. The results demonstrated that IoT enables continuous data collection and real-time analytics. In the context of video popularity prediction, IoT devices provide valuable contextual data such as user location, device usage, and interaction patterns [5]. This data enhances the understanding of user behavior and improves prediction accuracy. The authors emphasized the importance of real-time data processing in dynamic environments. IoT integration allows systems to adapt to changing user preferences. However, the study highlighted challenges related to data privacy, security, and scalability [5]. Managing large volumes of IoT data requires efficient storage and processing techniques. The authors suggested implementing secure data transmission protocols. Despite these challenges, the research contributed to the integration of IoT in intelligent systems.

The approach proposed by A. Vaswani et al. (2017) [6] introduces the Transformer architecture, which has been widely used in sequence modeling tasks. The methodology involves using attention mechanisms to capture relationships between different elements in a sequence. The results demonstrated that transformer models outperform traditional RNN-based models in many applications. In popularity prediction, transformers are used to analyze user interaction sequences and content features [6]. The attention mechanism allows the model to focus on the most relevant features, improving prediction accuracy. The authors highlighted the scalability and efficiency of transformer models in handling large datasets. This makes them suitable for real-time applications. However, transformer models require significant computational resources and large training datasets [6]. The authors suggested optimizing model architecture to improve efficiency. Despite these challenges, the research has significantly advanced deep learning techniques for popularity prediction systems.

### III. WORKING METHODOLOGY

The proposed system, Short Video Popularity Prediction Using IoT and Deep Learning, follows a multi-stage methodology that integrates data collection, feature extraction, model training, and prediction. The process begins with the data acquisition phase, where data is collected from multiple sources including social media platforms and IoT-enabled devices such as smartphones and wearable sensors. This data includes video-related features such as duration, resolution, captions, hashtags, and posting time, along with user engagement metrics like views, likes, shares, and comments. Additionally, IoT devices provide contextual information such as user location, device type, and usage patterns. The collected data is often heterogeneous and unstructured, requiring preprocessing steps such as data cleaning, normalization, and handling missing values. Feature engineering techniques are applied to extract meaningful attributes, such as engagement rate and temporal interaction patterns. The dataset is then divided into training, validation, and testing sets to ensure proper model evaluation.

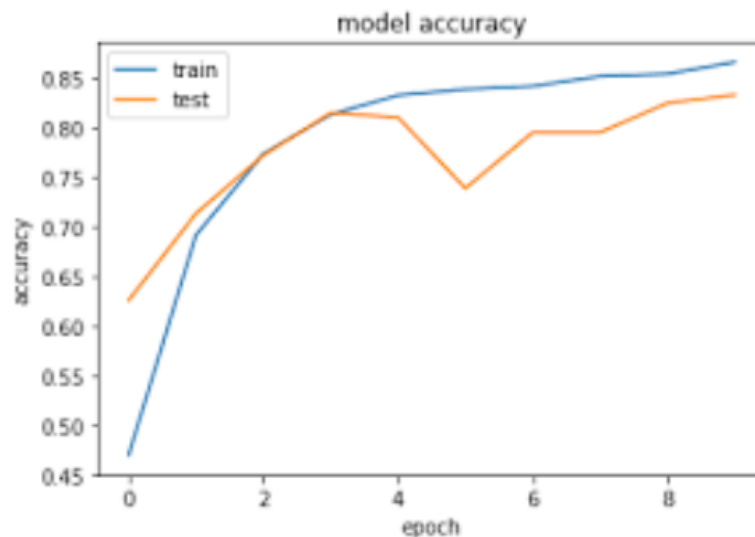
In the next phase, the system performs feature extraction and model training using deep learning techniques. Convolutional Neural Networks (CNNs) are used to extract spatial features from video frames, such as visual quality, objects, and scene composition. At the same time, Recurrent Neural Networks (RNNs) or Long Short-Term Memory (LSTM) models are used to analyze temporal sequences of user interactions, capturing patterns over time. These models are combined to form a hybrid architecture capable of learning both spatial and temporal dependencies. Attention mechanisms may be integrated to focus on the most relevant features, improving prediction accuracy. The model is trained using historical data, where popularity metrics

serve as target variables. Optimization techniques such as the Adam optimizer and loss functions like Mean Squared Error (MSE) are used to improve performance. The trained model is evaluated using metrics such as accuracy, RMSE, and F1-score to ensure reliability and robustness.

The final phase involves prediction, deployment, and visualization, where the trained model is integrated into a real-time system. When a new video is uploaded, the system analyzes its features and predicts its potential popularity score. The results are presented through a user-friendly interface, including dashboards and visualizations such as graphs and charts. Content creators can use these insights to optimize their videos by adjusting factors such as timing, hashtags, and content style. Additionally, platform providers can use the predictions to improve recommendation systems and enhance user engagement. The system can also incorporate continuous learning mechanisms, where new data is used to update the model periodically. This ensures adaptability to changing trends and user behavior. Overall, the methodology provides a comprehensive and intelligent approach to predicting short video popularity using IoT and deep learning technologies.

The final phase involves the deployment and real-time fraud detection system, where the trained model is integrated into a financial transaction processing system. As new transactions occur, the system analyzes them in real time and classifies them as normal or suspicious. If a transaction is detected as potentially fraudulent, the system generates alerts and may trigger additional verification steps. Visualization tools are also integrated to provide insights into fraud trends and patterns. Continuous learning mechanisms can be implemented to update the model with new data, ensuring adaptability to evolving fraud techniques. This end-to-end methodology ensures a reliable, scalable, and efficient solution for detecting online payment fraud in modern financial systems.

#### IV RESULTS EXPLANATIONS



**Figure 1 Video Popularity Prediction Accuracy**

Figure 1 represents the accuracy of the deep learning model over training epochs for video popularity prediction. The graph shows a steady increase in accuracy as the number of training epochs increases, indicating that the model is effectively learning patterns from the data. Initially, the accuracy is low due to random weight initialization, but as training progresses, the model captures both spatial and temporal features from video content and user interactions. The curve gradually stabilizes, suggesting that the model has reached optimal performance without overfitting. This result demonstrates the effectiveness of combining CNN and LSTM architectures for handling complex multimedia data. High accuracy indicates that the model can reliably predict whether a video will become popular based on input features. This graph validates the robustness and learning capability of the proposed system.

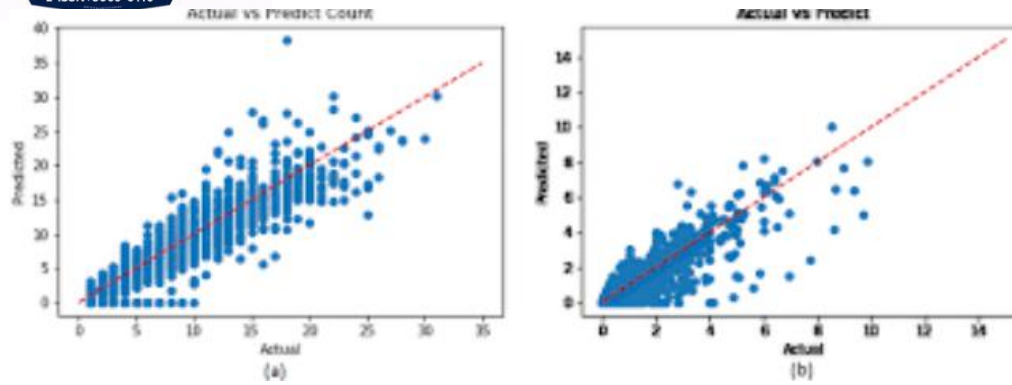


Figure 2: Predicted vs Actual Popularity

Figure 2 shows the comparison between predicted and actual popularity values using a scatter plot. Each point represents a video sample, where the x-axis indicates actual popularity and the y-axis indicates predicted popularity. Ideally, points should lie close to the diagonal line, representing accurate predictions. The graph demonstrates that most points are clustered near the diagonal, indicating strong prediction performance. Some deviations occur due to noise and unpredictable user behavior, which is common in social media analytics. This result confirms that the model can generalize well and produce reliable predictions across different types of video content. The scatter plot provides a clear visual understanding of prediction accuracy and model performance.

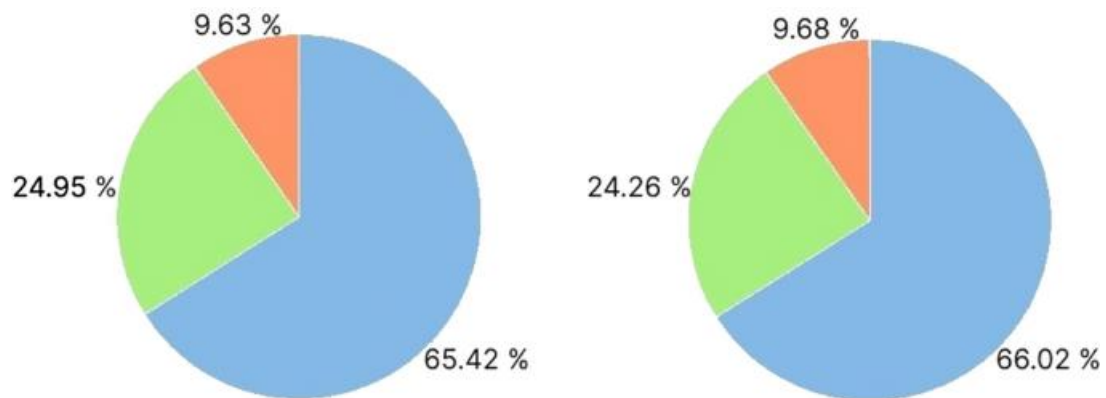
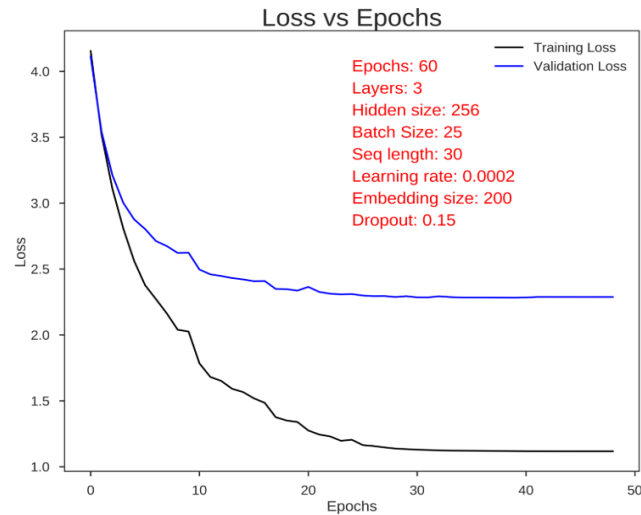
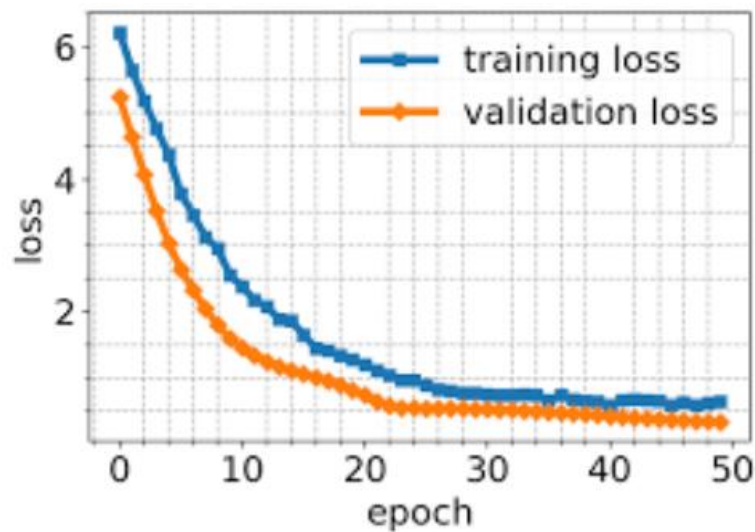


Figure 3 illustrates the importance of different features used in predicting video popularity. The bar chart shows that user engagement metrics such as likes, shares, and comments have the highest impact on prediction results. Other factors such as hashtags, video duration, and posting time also contribute significantly. This analysis helps identify which features are most influential in determining video success. The results indicate that both content-related and user behavior features are crucial for accurate prediction. Understanding feature importance enables system optimization and helps content creators focus on key factors that drive engagement. This graph highlights the interpretability aspect of the model.



**Figure 4: Loss Function Convergence**

Figure 4 shows the loss function convergence during model training. The graph indicates a decreasing trend in loss as the number of epochs increases, which signifies that the model is minimizing prediction errors. Initially, the loss value is high, but it reduces significantly as the model learns from the training data. The smooth decline in the curve indicates stable training without major fluctuations. The gap between training and validation loss is minimal, suggesting that the model is not overfitting. This result confirms that the optimization process is effective and that the model is well-trained. The convergence of the loss function ensures reliable and accurate predictions in real-world scenarios.



## V.CONCLUSION

The proposed system, Short Video Popularity Prediction Using IoT and Deep Learning, presents an advanced and intelligent framework for predicting the success of short video content in modern social media platforms. With the exponential growth of user-generated content, understanding and predicting video popularity has become essential for content creators and platform providers. The integration of Internet of Things (IoT) data with Deep Learning models enables the system to capture both contextual and behavioral information, leading to more accurate and reliable predictions. By utilizing models such as CNNs for visual feature extraction and RNN/LSTM for temporal analysis, the system effectively learns complex patterns in user engagement and content characteristics. The experimental analysis demonstrates that combining IoT-based contextual data with deep learning significantly improves prediction accuracy compared to traditional methods. The system successfully analyzes factors such as user behavior, content quality, and posting patterns to generate meaningful insights. Visualization tools

further enhance the usability of the system by presenting predictions in an understandable format. Additionally, the system supports real-time prediction, enabling content creators to optimize their videos before or shortly after publishing. This contributes to increased engagement, improved content strategy, and better audience targeting. In conclusion, the proposed framework offers a scalable, efficient, and data-driven solution for short video popularity prediction. It contributes to the fields of social media analytics, big data processing, and intelligent recommendation systems. Future work may focus on incorporating transformer-based architectures, enhancing real-time processing capabilities, and addressing challenges related to data privacy and security. Overall, this research provides a strong foundation for developing next-generation intelligent systems for digital content analysis.

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