# PREDICTING SOCIAL MEDIA POPULARITY: A MACHINE LEARNING APPROACH FOR MULTI-PLATFORM ENGAGEMENT FORECASTING

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**Abstract**
*The rapid growth of social media platform had changed how information spread and how user interaction evolves forecasting the popularity of content has become essential for content creators, advertisers and researchers .This paper reviews and summaries the latest machine learning methods used to predict popularity across multiple platforms, focusing on multimodal integration, graph neural network(GNN) transformer-based model and diffusion models it provides a detailed review of literature from 2020 to 2025 and highlights measure difficulty such as predicting popularity early on platform specific biases and the need for models that can be understood. The study also suggests future research direction emphasizing the development of models that are explainable, adaptable, and ethically sound.*
***Keywords:*** *Social media, popularity prediction machine learning, engagement forecasting, deep learning, multi- platform analysis*

## 1.Introduction

Social media platform such as Facebook, Instagram, Twitter (X), YouTube tik Tok have billions of active users, daily producing large amounts of user- engagement related data. Understanding the factors that contribute to the success of content major through likes, shares and views is essential for communication strategies advertising and public conversations [1]. Predicting the popularity of social media content involves using early signals and contextual factors to estimate level of engagement. How ever the differences in how each platform operates user behaviour and the type of content they share, make this task complex [2]. The same content might go viral on one platform but go unnoticed on another. Machine learning (ML) methods have evolved from early models like regression to more advanced techniques such as deep learning, multimodal fusion and network base systems.

The goal of this paper is to review theoretical and empirical studies on popularity prediction and identify the types of features and models used in predicting popularity across platform, discuss current challenges and future opportunities for creative models that are interpretable and transferable.

## 2. Literature Review

Earlier studies were based on information diffusion theory, which models the spread of information through network [1]. Classical models like SVR and threshold model provided useful insights but did not account for the complex interaction driven by the recommendation system, multimedia content and cross- platform sharing.

Traditional approaches (2010-2018) use linear regression, random forest and support vector machines (SVMs) with features based on text, time and user activity [2]. While these models were interpretable to capture the deep semantic relationship or how engagement evolves over time.

The introduction of deep learning (2018–2022) brought new data driven method that can better model the dynamic of time and visual elements. Recurrent neural networks (RNNs), Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs) become popular for analysing user behaviour and visual content [3][4]. Multimodal fusion – combining image, text and metadata - prove to be effective in improving accuracy.

Work by Almutairi and Rawat [5], and Chen et al. [6] Show that this method led to better performance. Graph Neural Networks (GNNs) have further improved results by considering the structure of social network and user interactions. Studies by Jiao et al. [7] and Ma et al. [8] demonstrate that including network topology allows accurate modelling of how content spread and how engagement is shared.

Transformer– based models (2022-2025), such as CLIP, BLIP and ViLT introduce self-attention mechanism that help with cross- modal alignment [6] [9]. These models perform better than other methods when find tune for social media data according to Hsu et al. [9].

More recently, diffusion-based models (2024-2025) have shifted the focus toward probabilistic forecasting. Li et.al.[10] and Jing et al. [11] have developed model that simulate multiple possible outcomes of engagement, helping to provide predictions that account for uncertainty.

Despite these advancements, several challenges still exist. Differences between platform inconsistency in the meaning of multimodal features, and a lack of transparency in models make generalization difficult [3],[6]. More recent research emphasizes the need for explainable AI, causal analysis and disentangled representations to better understand the factor behind popular content.[7]

represent a major shift toward probabilistic forecasting. Works by Li et al. [10] and Jing et al. [11] simulate multiple future engagement trajectories, providing uncertainty-aware predictions.

Despite advancements, open challenges remain. Cross-platform variability, semantic inconsistency between modalities, and lack of interpretability hinder model generalization [3], [6]. Recent work emphasizes explainable AI, causal modelling, and disentangled representations to enhance understanding of what drives popularity [7].

## 3. Methodological Framework

### 3.1 Problem Definition

Predicting popularity is usually treated as a regression or classification problem. The goal is to estimate the engagement of Matrix-like views, likes, and comments based on data available shortly after content is posted. Key subtasks include:

**Early-stage prediction:** estimating the final popularity from the initial responses

**Cascade modelling:** analysing the growth pattern of engagement.

**Cross-platform forecasting:** predicting how content will perform across different platforms [1][7].

### 3.2 Feature Categories

**Content Features:** include the tone and sentiment of the content, the topic, visual quality, and how will the image match the text [3],[9].

**Temporal Features:** these include the time the content was posted how quickly engagement starts and how deep the engagement cascades [10].

**User Features:** these include the number of followers, the user activity history and their influence.

**Network Features:** these involve the central role of the user in the network, the path of content propagation, and the impact of community dynamics [8].

**Platform Specific Features:** These include the platform's recommendation algorithms the type of media (text, video) and how users interact on that platform [2][6].

### 3.3 Machine Learning Techniques:

**Classical machine learning:** Models such as regression, random forests and Gradient boosting (including XGBoost and Light GBM) still serve as strong base lines from my especially when working with engineered features [2].

**Deep Learning:** technique such as LSTMs and GRUs are used to capture temporal pattern, while CNNs process visual data [3],[4].

**GNNs:** Frameworks like GCN and graph sage help in understanding the structural influence within a network [7],[8].

**Transformers:** These models use cross model attention to combine text and image data effectively [6][9].

**Diffusion Models:** They simulate the likely outcome of engagement in a probabilistic way especially when dealing with uncertainty [10][11].

**Hybrid/Ensemble Models:** By combining Deep and classical models, these approaches provide reliable performance across different platform settings [4].

## 4. Multi-Platform Engagement Modelling:

Each platform operates with its own set of rules, user base, and engagement dynamics. Therefore, predicting how content will perform across different platforms require flexible modelling techniques. Platform-specific models are Tailored to predict performance on individual platform [2]. Multi-task learning help in extracting common features while platform - specific output are used for final predictions. Disentangled models separate general content quality platform specific dynamics, making it easier to transfer models across platform [3]. domain adaptation technique such as adversarial training, help in dealing with differences in data between platforms [3]. Dataset like the news engagement data set [2] and the SMP challenge benchmark [6] support the evaluation of these models although their use is limited because of API restrictions.

## 5. Evaluation framework:

The evaluation methods depend on the type of task:

- For regression tasks, common metrics include the mean absolute error (MAE), root mean square error (RMSE) and spearman rank correlation (SRC).
- For Classification Problems, F1-Score, Accuracy, and AUC-ROC are used.
- For ranking tasks, metrics such as Precision@K and NDCG are employed [4].

Time-based train-test splits are used to avoid data leakage, and early-stage prediction test simulate real world forecasting performance [10]. Ablation studies help to understand the impact of different feature groups [9].

## 6. Challenges and Opportunities

1. **Early–stage forecasting:** It is difficult because the initial data is limited and uncertain diffusion and generative models can help produce this uncertainty [10].
2. **Cross platform generalization:** It is a challenge due to differences in user behaviour and way is brought from rank contain [3].
3. **Data Skew:** where popularity follows heavy teller distribution make it hard to model techniques like balance sampling and log transformation help the planning models left [6].
4. **Interpretability:** Deep model Lack of transparency making it hard to understand their decisions. attention visualisation and causal models can improve interpretability [7].
5. **Data Access and privacy:** Concern limit the ability to reproduce models federated learning offers some solutions to this problem [1].
6. **Ethical Concerns:** It arises from the potential for predictive models to amplifier biases or spread misinformation therefore there is a growing meet for fair and responsible AI systems [11].

## 7. Future Scope:

- **Casual modelling:** Find the real cause-and -effect relationship that drive content popularity. Explainable multimodal AI: show how different features contribute to prediction and highlight where the model focuses its attention.
- **Probabilistic forecasting:** Use diffusion –based technique to include uncertainty in forecasts.
- **Cross -platform adaptation:** build hybrid models that combine GNNs -transformers for flexible transfer learning across platform.
- **Real -Time Prediction:** keep models updated continuously and handle changes in data patterns over time.
- **Responsible AI:** make sure fairness and transparency are built into the algorithm that drive user engagement [7][11].

## 8. Conclusion:

Social media popularity prediction has advanced from simple regression method to complex multimodal and Graph-based architecture. deep learning graph neural network and transformer model have greatly improved the accuracy of prediction while diffusion model enable forecast, uncertainty to account. Despite these advances there are still challenges when it comes to understanding how models make decisions, adopting them across different platform and ensuring ethical use.

Future system needs to be clear, adaptable to multiple platforms and able to explain the decisions in cause- and -effect way. These ensure that AI driven prediction is fair and used responsibly. The field of predicting social media popular is growing rapidly thanks to both academic research and real-world application which is development will likely come from strong crossword from which learning method accessible. AI techniques causal analysis and ethical guidelines for responsible prediction as social media continues to influence how information spread and public conversation happens, the ability to understand and predict what contain become popular will remain a key area of research with wide ranging effect on technology and policy.

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