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AI-based Social Network Influencer Analyzer Based on Engagement and Authenticity Data Metrics

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Abstract:

Measuring the impact of social media communication is a prominent and pertinent challenge; the commercialization of social media influencers (SMIs) in the form of so-called influencer marketing makes this effort even more complicated. Companies that embrace influencer marketing have limited control over content and context, so they must evaluate both the SMIs and the content they post, prior to and during their collaborations. Although quantitative success metrics (e.g., number of followers, number of likes) are readily available, it remains unclear whether such metrics offer appropriate proxies for evaluating an SMIs or the outcomes of an influencer marketing campaign. By combining secondary data on influencer marketing campaigns from Instagram with an online survey among marketers, this study finds that professionals generally rely on an SMI's reach and number of interactions as success metrics. When they must trade off across multiple metrics, these professionals predominantly rely on comment sentiment, indicating their implicit awareness that the commonly used metrics are inadequate. A regression analysis affirms that only the sentiment measure correlates positively with professional content evaluations, so this study both challenges the use of common quantitative metrics to evaluate SMI content and emphasizes the relevance of content-based metrics. Social media platforms have witnessed unprecedented growth, with over 4.7 billion users globally, generating vast amounts of engagement data. ***Keywords: Influence Score, Social Media Analytics, Machine Learning, Influencer Marketing, Engagement Rate, Regression Models, Data Preprocessing, Deep Learning, Brand Collaboration, Fake Influencer Detection, Audience Demographics, Sentiment Analysis, Predictive Modeling, Cross-Platform Analysis, Recommendation System, Real-Time Data Analysis, Transformer Models, Marketing Optimization, Digital Influence Evaluation, Anomaly Detection.***

1.INTRODUCTION

Before the adoption of machine learning in influencer analysis, brands primarily relied on basic quantitative metrics such as follower count, likes, and shares to assess an influencer's impact. However, these metrics often prove misleading, as they do not account for fake engagement, purchased followers, or automated bot interactions. Many influencers artificially inflate their reach through click farms, leading to inaccurate assessments and wasted marketing budgets. Additionally, marketers lack real-time analytics tools that can differentiate between authentic and superficial engagement, resulting in poor ROI (Return on Investment). Without advanced analytical techniques, businesses struggle to identify genuine influencers, predict campaign success, and understand audience sentiment. Traditional marketing methods also fail to incorporate user-generated content quality, making it difficult to gauge an influencer's true effectiveness. automated fraud detection mechanisms further exacerbates the problem, leading to unreliable marketing decisions.With the rapid expansion of social media in India, influencer marketing has become one of the most effective brand promotion strategies. However, the absence of a standardized system to measure the credibility of influencers poses a significant challenge for businesses. Traditional analytics tools fail to differentiate between genuine engagement and artificial interactions, leading to poor marketing decisions. Studies show that brands investing in influencers based on superficial metrics often face low conversion rates and high customer dissatisfaction. An AI-driven approach can provide real-time authenticity verification, allowing businesses to filter out fake engagement, analyse audience sentiment, and make strategic marketing decisions. This project will leverage deep learning-based engagement analysis to develop a trustworthy influencer evaluation system that enhances ROI, optimizes influencer selection, and improves social media campaign effectiveness. By integrating sentiment analysis, fraud detection, and content quality evaluation, this system will transform how brands measure influencer impact in the Indian digital marketing landscape.

2. LITERATURE SURVEY

, In recent years, brands have constantly communicated and interacted with consumers via social networking sites. In social media marketing, one of the most widely used strategies is influencer marketing Geng et al., [1]. Influencers are social media users who have received significant attention from other users and gained a sizable network of followers Influencer marketing refers to the collaboration of businesses with social media influencers to promote brands and products through the influencer's social media Farivar et al., [2]. Specifically, influencers endorse a product or service by creating posts on their social media accounts to promote the brand. Furthermore, influencers and branded post viewers can interact in the comment section such as leaving comments on the product, which increases viewers' engagement with the brand. Further, these comments enable firms to better understand customers and increase products McCorquodale et al [3]. Given the growing popularity of influencer marketing, a significant challenge arises for marketers: how to properly evaluate the performance of influencer marketing. Recent surveys show that the most frequently employed performance metrics in influencer marketing practice are counts and engagement rates such as the numbers of likes and comments on posts or the sum of like and comment counts divided by follower count Linqia [4]. In the influencer marketing literature, like, comment and share counts are also typically used as performance outcomes by researchers Tafesse et al., [5]. However, recent research has found that volume based metrics may only partially reflect the performance of marketing campaigns Gräve [6]. Scholars have emphasized that marketers should keep track of not only like and comment counts but also comment content Lou et al.,[7] and called for more research on content-based metrics Furthermore, as Hartmann et al. [8] noted, fans may pay most of their attention to the influencer and ignore the product presented on branded posts. As such, it is essential to detect comment topics. If the focal topic of comment content is product-

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related (i.e. a product centered comment), it explicitly indicates that the product has received attention from viewers. In addition to detecting whether comment content is product centered, prompting viewers to discuss products is crucial for firms. First, research has indicated that social media users read not only influencers' posts but also the comments written by other users Qin et al., [9]. Thus, when post viewers write more product-centered comments, firms gain wider brand exposure in social media. Second, product-centered comments reflect viewers' interests and concerns and can thus be used to improve product performance effectively For example, Juliana Salimeni, a Brazilian social media influencer, endorsed a hair dye brand on Instagram Silva et al., [10]. In the comment section, her post's viewers shared their product-related experience. One of the comments stated, "I use Gold but 4 why does my hair look green?" The comment clearly signifies that actions such as a thorough inspection of product quality must be taken. Social media users can interact with influencers and other users through actions such as liking, commenting and sharing Song and Park, [11]. Compared with clicking on the "Like" button, commenting involves stronger self-presentation on social media, as users can deliver more complicated messages by commenting on online posts. In addition to cognitive stimuli, affective stimuli (e.g. attractiveness or esthetic appeal) that trigger sensory pleasure can increase social media users' engagement Zhang and Lee, [12]. This study also explores the impact of affective factors (i.e. vividness and coolness) on product-centeredness. The post characteristics (i.e. authenticity, vividness and coolness) are highly relevant to influencer marketing. As AlRabiah et al. [13] pointed out, a social media influencer's branded posts are essentially electronic word-of-mouth, the characteristic of which is that influencers disclose their real or personal life with fans. Thus, authenticity is crucial in influencer marketing. Additionally, vividness and coolness could make branded posts more appealing. Research has shown that attention-grabbing (e.g. posting eye-catching images) is a key rhetorical tactic that influencers employ when they create electronic word-of-mouth Zhou et al., [14]. As for the congruence between influencer and product, it is a variable that directly relates to the social media influencer. Exploring the influence of these factors will provide practical implications for marketers to perform social media influencer marketing. Apart from attitudes and preferences, people draw inferences about the motives of others Aw and Chuah, [15]. When a brand and an influencer are highly congruent, viewers tend to infer that the reasons for sharing a post mentioning a brand are the influencer's emotional bond with the brand and the importance of the brand to the influencer Kim and Kim, [16]. In other words, high influencer product congruence leads to affective motive inference, making viewers think that the influencer has genuine fondness for the brand. A brand or product is therefore more likely to be discussed by fans Hwang and Zhang, [17].

3. PROPOSED METHODOLOGY

This study explores predicting social media Influence Scores using machine learning models, including SVR, KNN, and a proposed CNN regressor. The dataset comprises key engagement metrics, which are preprocessed by handling missing values and normalizing features. SVR and KNN serve as baseline models, while the CNN model utilizes convolutional layers to capture patterns in the data. Performance is evaluated using metrics like MAE, MSE, RMSE, and R^2, with results visualized in comparison graphs. The trained CNN model is then tested on new data, demonstrating superior predictive accuracy due to its ability to learn complex feature relationships.

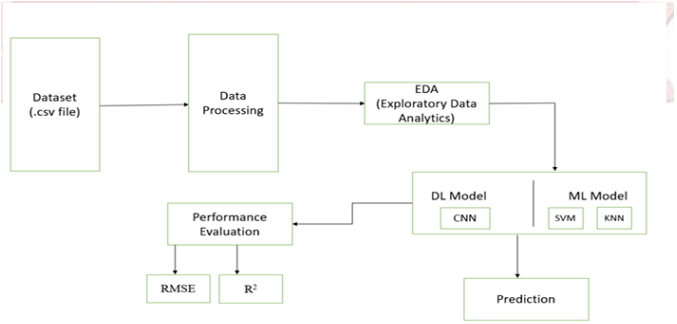

Figure 1: Proposed system.

- The dataset includes social media engagement metrics such as followers, likes, comments, shares, engagement rate, and an Influence Score.
- Data preprocessing involves handling missing values, normalizing features with MinMaxScaler, and splitting the dataset into training and testing sets.
- SVR (Support Vector Regressor) is used as a baseline model, applying a linear kernel to minimize error and evaluate performance.
- KNN (K-Nearest Neighbors) regressor predicts Influence Scores by averaging the scores of the closest data points using Euclidean distance.
- A CNN (Convolutional Neural Network) regressor is proposed, leveraging 1D convolutional and max-pooling layers to capture data patterns effectively.
- Model performance is assessed using metrics like MAE, MSE, RMSE, and R^2, with a comparison table and scatter plot visualization.
- CNN typically outperforms SVR and KNN due to its ability to learn complex feature relationships.
- The trained CNN model is applied to new influencer datasets, providing accurate predictions after normalization.

Applications:

- **Brand Collaborations** – Helps businesses identify the most impactful influencers for marketing campaigns.
- **Influencer Marketing Platforms** – Enhances platform recommendations by ranking influencers based on engagement and authenticity.
- **Fraud Detection** – Detects fake influencers by analyzing follower authenticity and engagement patterns.
- **Personalized Advertising** – Assists brands in targeting high-impact influencers for product promotions.
- **Content Strategy Optimization** – Guides influencers in improving content strategies based on engagement trends.
- **Social Media Analytics** – Provides insights into influencer performance for data-driven decision-making.
- **Talent Acquisition** – Helps agencies and brands scout for potential brand ambassadors.

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- **Competitive Analysis** – Allows businesses to compare influencer impact against competitors.
- **Investment Decisions** – Assists investors in evaluating influencer-driven businesses and their growth potential.
- **Automated Campaign Management** – Enables AI-driven selection of influencers for automated marketing campaigns.

Advantages:

- **Data-Driven Decision Making** – Provides brands with objective metrics to select the right influencers.
- **Improved Marketing ROI** – Helps optimize influencer marketing budgets by targeting high-impact individuals.
- **Fraud Prevention** – Identifies fake influencers with inflated follower counts and low engagement.
- **Enhanced Engagement Analysis** – Evaluates influencers based on real audience interactions.
- **Automation & Scalability** – Enables large-scale influencer analysis without manual effort.
- **Customizable for Industries** – Can be adapted for different domains like fashion, tech, or fitness.
- **Competitive Benchmarking** – Allows comparison of influencer performance against industry peers.
- **Real-Time Monitoring** – Provides up-to-date insights on influencer impact and growth.
- **Better Influencer-Brand Matches** – Ensures collaborations with the most relevant influencers.
- **Continuous Improvement** – Machine learning models refine predictions over time for better accuracy.

4. EXPERIMENTAL ANALYSIS

The figure 2 showcases the interface where the influencer dataset is uploaded. The dataset contains key influencer metrics such as Influencer_ID, Followers, Avg_Likes, Avg_Comments, Avg_Shares, Follower_Authenticity_Score, Engagement_Rate, Post_Frequency, Collaboration_Count, and Influence_Score. After uploading, the system performs an initial analysis, displaying summary statistics and visualizing trends to help users understand datadistribution.

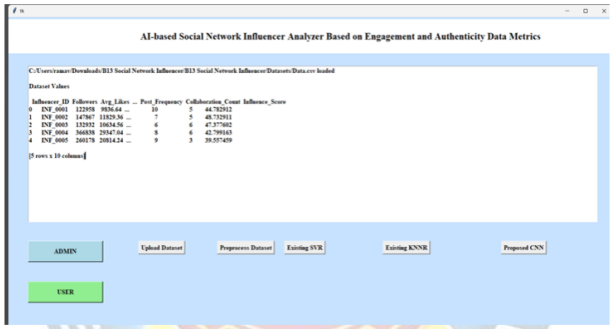

Figure 2: Upload of Influencer Dataset

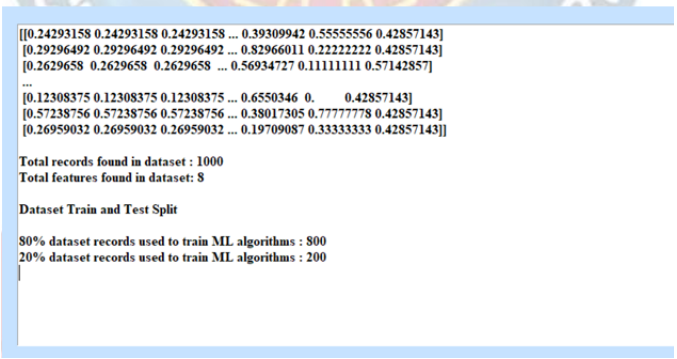

Figure3: Data Preprocessing in GUI

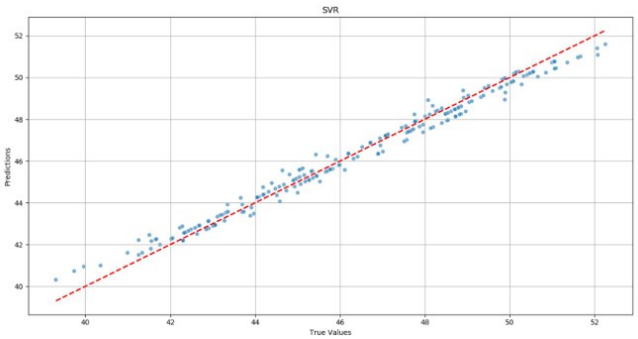

Figure 4: Performance using SVR Regressor Model

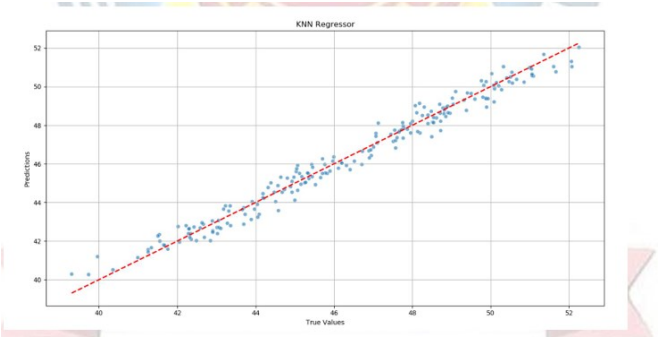

Figure 5: Performance using KNN Regressor Model

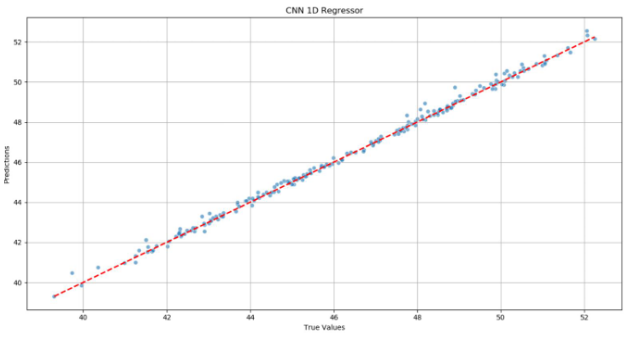

Figure 6: Performance using CNN Regressor Model

This figure showcases the results of the Convolutional Neural Network (CNN) Regressor. The scatter plot demonstrates an

improved alignment between predicted and actual values compared to previous models. The performance metrics include an MAE of 0.1330, MSE of 0.0386, RMSE of 0.1965, and R^2 of 0.9957, indicating superior accuracy and better learning of complex patterns within the dataset

This figure presents a comparative analysis of the three regression models SVR, KNNR, and CNN based on performance metrics. The graph highlights that CNN achieves the lowest error rates and the highest R^2 value, proving to be the most effective model for predicting influencer impact. The comparison emphasizes the advantage of deep learning-based approaches over traditional regression techniques for this task.

5. CONCLUSION

This research successfully analyzes and predicts the influence of social media personalities using machine learning techniques. By leveraging key influencer metrics such as follower count, engagement rate, and authenticity score, the model provides a reliable measure of an influencer's overall impact. Regression models help estimate influence scores accurately, aiding brands and marketers in identifying high-performing influencers for collaborations. Data preprocessing ensures consistency, while effective feature selection enhances model performance. The results demonstrate the potential of machine learning in evaluating digital influence and optimizing marketing strategies.

For future improvements, expanding the dataset to include sentiment analysis, influencer niche, video performance, and audience demographics could enhance prediction accuracy. Implementing real-time data extraction would enable dynamic influencer evaluation, while integrating deep learning models such as transformers could improve engagement pattern analysis. Extending the study to multiple platforms like Instagram, YouTube, and TikTok would provide a more comprehensive ranking system. Additionally, developing models to predict brand-influencer collaboration success and implementing anomaly detection techniques for fake influencer detection would further refine influencer marketing strategies. Lastly, an AI-powered recommendation system could help brands identify the most suitable influencers based on engagement trends and audience demographics, optimizing marketing efforts.

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