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Detecting Influencer Authenticity on Social Media Platforms using Machine Learning and Natural Language Processing Techniques

Sambhavi Singh
B.Tech CSE, Amity University Chhattisgarh, India
rajputsam2005@gmail.com

shikha Tiwari
Amity University Chhattisgarh, India
Stiwari@rpr.amity.edu

Abstract

The growth of social media platforms has greatly increased the use of influencer marketing as an important strategy for brand promotion. However, the increasing presence of fake followers, automated bots, and manipulated engagement has made it difficult to accurately assess the authenticity of influencers. This creates serious challenges for brands when selecting trustworthy influencers for collaborations.

To address this issue, this study proposes an Influencer Authenticity Analyzer that uses Machine Learning and Natural Language Processing (NLP) techniques to evaluate influencer credibility. The system analyzes numerical data such as follower count, likes, and comments, along with textual data including captions and user interactions. NLP techniques such as sentiment analysis and keyword extraction are used to understand content quality, while engagement metrics help identify unusual or suspicious patterns.

In addition, the system includes features such as fake follower detection, fake comment identification, and influencer comparison, providing a more complete evaluation. The results are presented through an interactive dashboard with graphical visualizations, making it easier for users to interpret the findings. The system generates an authenticity score along with a classification result, helping users distinguish between genuine and fake influencers.

Overall, the proposed approach offers a practical and effective solution for improving transparency in influencer marketing and supporting data-driven decision-making.

Keywords

Influencer Authenticity, Machine Learning, Natural Language Processing, Sentiment Analysis, Fake Followers Detection, Engagement Analysis, Social Media Analytics

1. Introduction

In recent times, the rapid-fire advancement of digital technologies has significantly converted the way businesses communicate with their cult. Social media platforms similar as Instagram, Twitter, and others have come central to ultramodern marketing strategies. Among colourful digital marketing ways, influencer marketing has surfaced as one of the most effective approaches for reaching targeted cult and erecting brand trust. Influencers, who are individualities with a strong online presence and a large follower base, have the capability to shape opinions, influence purchasing opinions, and produce meaningful engagement with druggies.

still, with the adding fashionability of influencer marketing, several challenges have also surfaced. One of the most critical issues is the growing presence of fake influencers and manipulated engagement. numerous influencers instinctively increase their follower count through bought followers or automated bots. also, engagement criteria similar as likes, commentary, and shares can be generated using automated tools, creating a false print of fashionability and influence. This not only reduces the trustability of influencer marketing but also leads to fiscal losses for brands that invest in collaborations without vindicating authenticity.

Traditional styles of assessing influencers frequently calculate on introductory criteria similar as follower count or engagement rate. While these criteria give some position of sapience, they're no longer sufficient in relating genuine influencers. A high follower count doesn't inescapably indicate credibility, and engagement rates can be fluently manipulated. thus, there's a strong need for more advanced and intelligent systems that can dissect multiple aspects of influencer exertion to determine authenticity directly.

Artificial Intelligence (AI) and data wisdom ways offer promising results to this problem. Machine Learning algorithms are able of assaying large datasets and relating patterns that aren't fluently visible through homemade analysis. At the same time, Natural Language Processing (NLP) enables systems to understand and interpret textual data similar as captions, commentary, and stoner relations. By combining these technologies, it becomes possible to estimate both the quantitative and qualitative aspects of influencer exertion.

The proposed Influencer Authenticity Analyzer is developed to address these challenges by furnishing a comprehensive and data- driven result. The system analyzes numerical data similar as follower count, likes, and commentary, along with textual content using NLP ways like sentiment analysis and keyword discovery. It also incorporates features similar as fake follower discovery, fake comment identification, engagement rate computation, and influencer comparison. These features work together to give a detailed assessment of influencer authenticity.

In addition to logical capabilities, the system includes an interactive dashboard that presents results in a visual format using graphs and maps. This makes it easier for druggies to interpret the data and make informed opinions. The system is designed to be stoner-friendly and practical, making it suitable for real- world operations in digital marketing and brand operation.

Overall, this exploration aims to develop a dependable and effective system that can directly estimate influencer authenticity using advanced technologies. By integrating Machine literacy, Natural Language Processing, and engagement analysis, the proposed system provides a more comprehensive approach compared to traditional styles. This not only enhances translucency in influencer marketing but also supports better decision- making for brands and marketers, icing that collaborations are grounded on genuine influence rather than misleading criteria.

2. Literature Review

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The rapid expansion of social media platforms has created new opportunities for communication, marketing, and brand development. However, it has also introduced challenges related to authenticity and trust. As influencer marketing continues to grow, researchers have increasingly focused on developing methods to analyze user behavior, detect fake accounts, and evaluate influencer credibility. Various approaches based on Machine Learning, Natural Language Processing (NLP), and data analytics have been proposed to address these issues, each with its own advantages and limitations.

In the early stages of research, rule-based systems were commonly used to detect fake accounts and suspicious activities on social media platforms. These systems relied on predefined conditions such as sudden increases in follower count, low engagement rates, or repetitive posting behavior. Although these methods were simple and easy to implement, they lacked flexibility and adaptability. As social media platforms evolved, fake account strategies also became more advanced, making rule-based systems less effective in identifying complex patterns of fraudulent behavior.

To overcome these limitations, researchers began adopting Machine Learning techniques for detecting fake accounts and analyzing influencer data. Classification algorithms such as Logistic Regression, Decision Trees, Support Vector Machines, and Naive Bayes have been widely used to identify anomalies in user behavior. These models are capable of learning patterns from historical data and making predictions based on extracted features. For example, features such as follower-to-following ratio, account activity, posting frequency, and interaction levels have been used to distinguish between genuine users and fake accounts. While Machine Learning approaches offer improved accuracy compared to rule-based systems, they often rely heavily on numerical data and may overlook the importance of textual content.

At the same time, Natural Language Processing has gained significant attention for analyzing textual data generated on social media platforms. NLP techniques such as tokenization, stop-word removal, and sentiment analysis enable systems to process and interpret human language effectively. Sentiment analysis, in particular, has been widely used to understand the emotional tone of captions, comments, and posts. This helps in identifying whether audience interactions are meaningful or artificially generated. For instance, repetitive or overly positive comments may indicate bot activity rather than genuine engagement. However, many NLP-based systems primarily focus on text classification and do not incorporate engagement metrics or behavioral patterns, which limits their overall effectiveness.

Another important area of research involves the detection of social media bots and fake engagement. Bots are automated accounts designed to mimic human behavior and artificially increase likes, comments, and shares. Researchers have developed various techniques to identify such accounts by analyzing activity patterns, including posting intervals, duplicate comments, and lack of interaction diversity. Some studies have also explored network-based approaches, where relationships between users are analyzed to detect clusters of fake accounts. Although these methods are effective in identifying automated behavior, they often require large datasets and complex computational resources, making them less suitable for lightweight and real-time applications.

Engagement analysis has also been widely studied as a measure of influencer effectiveness. Engagement rate, calculated using metrics such as likes, comments, and follower count, is commonly used to evaluate how actively an audience interacts with an influencer's content. While this metric provides useful insights, it is not always a reliable indicator of authenticity. Influencers can artificially boost engagement through paid promotions or automated tools, which can lead to misleading conclusions if engagement metrics are considered in isolation.

Recent studies suggest that combining multiple analytical approaches can significantly improve the accuracy of detection systems. Hybrid models that integrate Machine Learning, Natural Language Processing, and behavioral analysis have shown promising results in identifying fake accounts and evaluating influencer authenticity. By analyzing both numerical data and textual content, these systems provide a more comprehensive understanding of user behavior.

3. Proposed System

The proposed Influencer Authenticity Analyzer is designed as amulti-functional and interactive system that evaluates the credibility of social media influencers using a combination of Machine Learning, Natural Language Processing, and engagement- grounded analytics. Unlike traditional systems that calculate on a single type of analysis, this system integrates multiple modules to give a comprehensive and accurate assessment of influencer authenticity.

The armature of the system is modular in nature, allowing different logical factors to work singly as well as collaboratively. Each module focuses on a specific aspect of influencer evaluation, similar as content analysis, engagement dimension, or behavioral pattern discovery. The following subsections describe each point of the proposed system in detail.

3.1 Single Influencer Analysis

The Single Influencer Analysis module is designed to evaluate the authenticity of an individual influencer based on user-provided data. In this module, the user inputs key parameters such as follower count, number of likes, number of comments, and textual content (captions or posts).

Once the data is provided, the system processes both numerical and textual information. Machine Learning models are applied to classify the influencer as genuine or potentially fake, while Natural Language Processing (NLP) techniques analyze the sentiment and quality of the textual content. The module generates an authenticity score along with visual outputs such as charts and graphs.

This feature is particularly useful for the quick evaluation of a single influencer before making collaboration decisions.

3.2 Multiple Influencer Comparison

The Multiple Influencer Comparison module allows users to analyze and compare multiple influencers simultaneously. This feature is especially useful for brands and marketers who need to select the most suitable influencer from a group of candidates.

In this module, the system collects data for multiple influencers and evaluates them using the same set of parameters. The results are presented in a comparative format, typically using bar charts or other graphical representations. Metrics such as engagement rate, authenticity score, and sentiment analysis are displayed side by side, enabling users to identify the best-performing influencer.

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This comparative analysis improves decision-making by providing a clear overview of the strengths and weaknesses of different influencers.

3.3 Fake Followers Detection

The Fake Followers Detection module focuses on identifying suspicious follower patterns that may indicate artificially inflated audience size. Many influencers purchase followers to appear more popular, but these followers often show abnormal behavior such as low interaction or inactive accounts.

This module analyzes patterns such as follower-to-engagement ratio, sudden spikes in follower growth, and inconsistencies in interaction levels. Machine Learning techniques are used to detect anomalies in these patterns. By identifying fake followers, the system ensures that the influencer's reach is genuine and not misleading. This feature is crucial for brands aiming to invest in authentic audience engagement rather than inflated numbers.

3.4 Fake Comment Detection

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3.5 Engagement Rate Calculation

Engagement rate is one of the most important indicators of an influencer's effectiveness. The Engagement Rate Calculation module measures the level of audience interaction based on key metrics such as likes, comments, and follower count.

The system calculates the engagement rate using standard formulas and evaluates whether the level of interaction is consistent with the size of the audience. A high number of followers combined with low engagement may indicate the presence of fake followers, while consistent engagement suggests a genuine and active audience.

This module provides both numerical results and graphical visualizations, helping users easily interpret the influencer's performance.

3.6 Search by Username

The Search by Username module enhances the usability of the system by allowing users to retrieve influencer data using their social media username. Instead of manually entering all parameters, users can simply input a username to access relevant information.

This module can be integrated with datasets or APIs to fetch influencer details automatically. It simplifies the data input process and reduces the chances of manual errors. By providing quick access to influencer data, this feature improves the overall efficiency and user experience of the system.

3.7 Dashboard Visualization

The Dashboard Visualization module is responsible for presenting the analysis results in an interactive and user-friendly format. Instead of displaying raw data, the system uses charts, graphs, and visual indicators to communicate insights effectively.

The dashboard includes features such as:

- *Bar charts for comparison*
- *Pie charts for engagement distribution*
- *Line graphs for trend analysis*
- *Score indicators for authenticity*

This module plays a crucial role in making the system accessible to non-technical users. It allows users to quickly understand the results and make informed decisions based on visual insights.

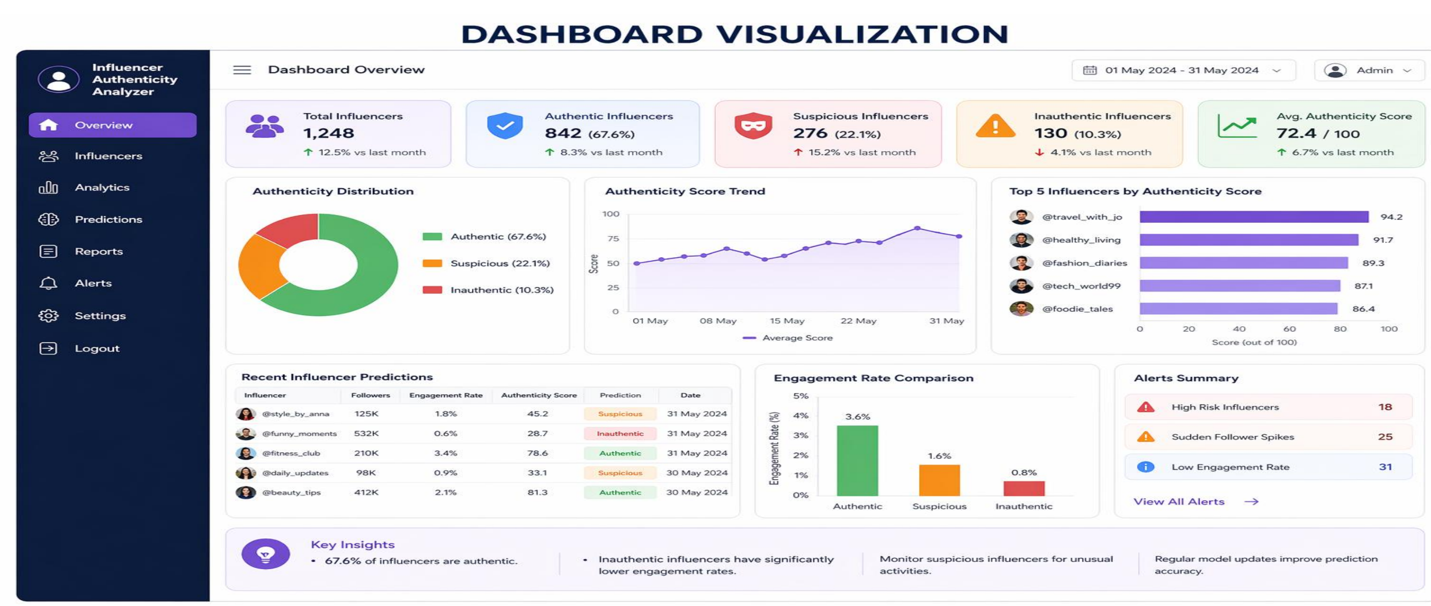

Figure 1:Dashboard Visualization

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3.8 System Integration and Workflow

All the modules are integrated into a unified system that follows a structured workflow. The process begins with data input, followed by preprocessing, feature extraction, and analysis using Machine Learning and Natural Language Processing (NLP) techniques. The results from different modules are then combined to generate a final authenticity score along with the classification output.

The modular design ensures flexibility, scalability, and ease of maintenance. Each component contributes to a specific aspect of the analysis, and together they provide a comprehensive evaluation of influencer authenticity.

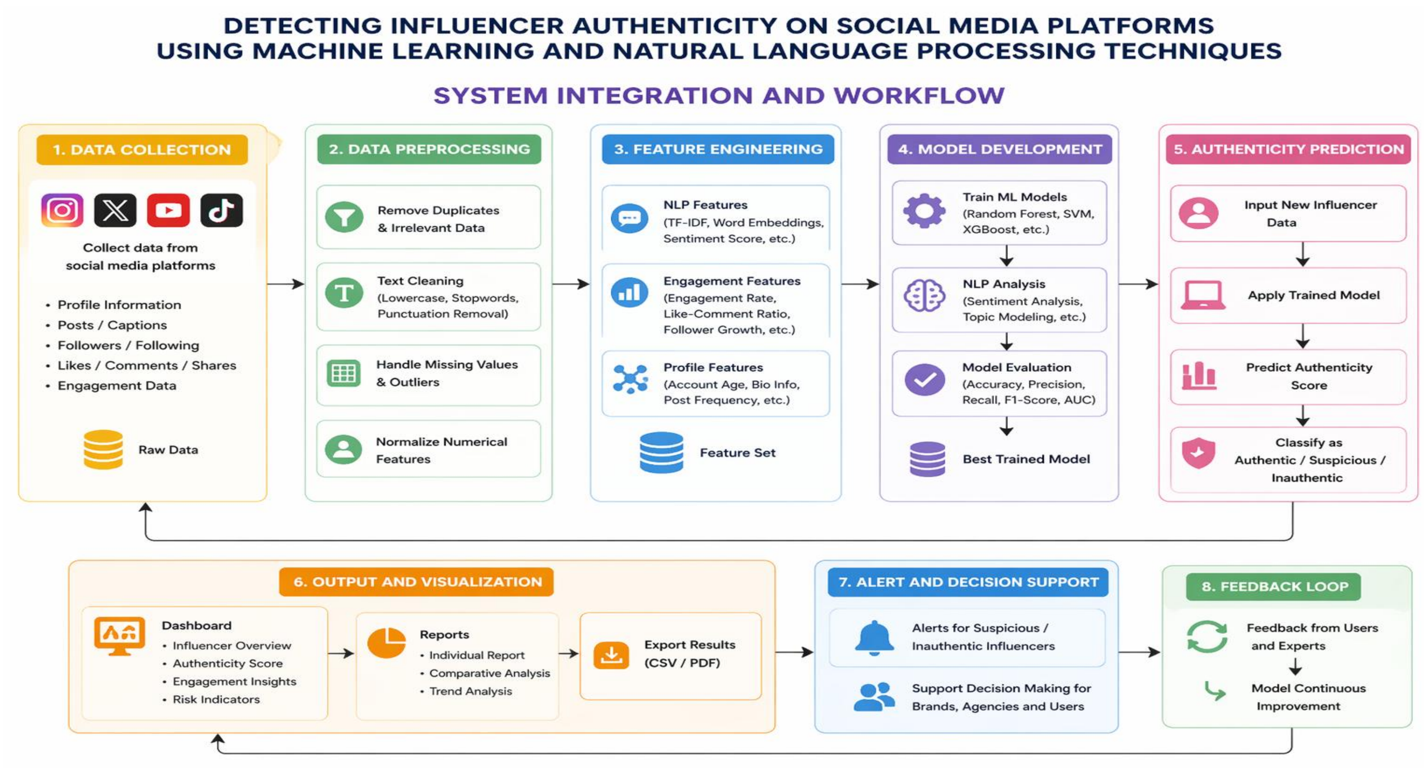

Figure 2: System Integration and Workflow

4. Methodology

The proposed Influencer Authenticity Analyzer follows a structured approach to estimate the credibility of social media influencers using Machine Learning and Natural Language Processing (NLP) ways. The system processes data in several stages, including data collection, preprocessing, point birth, model analysis, and affair generation.

The process begins with collecting influencer- related data similar as follower count, likes, commentary, and textual content like captions. This combination of numerical and textual data allows the system to dissect both engagement patterns and happy quality. Since social media data is frequently unshaped, it's first gutted and organized during the preprocessing stage. gratuitous symbols, missing values, and inapplicable information are removed, while textual data is simplified using ways similar as tokenization and stop- word junking.

In the point birth stage, important attributes are deduced from the reused data. Numerical features include engagement-related criteria similar as likes, commentary, and engagement rate, while textual features include sentiment score and keyword patterns attained using NLP. These features help in relating behavioral trends and detecting unusual or artificial exertion.

The uprooted features are also anatomized using Machine literacy models similar as Logistic Retrogression and Naive Bayes. These models classify influencers as genuine or fake by relating patterns in the data. The combination of numerical and textual analysis improves the delicacy of prognostications compared to single- system approaches.

Eventually, the system generates results in the form of an authenticity score and bracket affair. fresh perceptivity similar as sentiment analysis and engagement riteria are also handed. These results are displayed through a graphical dashboard, making it easier for druggies to understand and interpret the findings.

Overall, the methodology integrates Machine literacy and NLP into a unified frame, enabling accurate and effective evaluation of influencer authenticity.

5. System Architecture

The system architecture of the Influencer Authenticity Analyzer is designed using a modular and scalable approach to ensure efficient processing, analysis, and presentation of influencer data. The architecture is composed of several interconnected components, each responsible for a specific function in the overall workflow. This structured design improves flexibility, maintainability, and ease of future enhancements.

The process begins with the input module, which collects

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relevant influencer data. This includes numerical information such as follower count, likes, and comments, as well as textual content like captions and user comments. The system allows users to manually input data or retrieve it from available datasets, making it adaptable to different use cases.

The collected textual data is then processed in the NLP (Natural Language Processing) module. In this stage, various techniques such as sentiment analysis and keyword detection are applied to understand the nature and quality of the content. Sentiment analysis helps determine whether the text reflects positive, negative, or neutral emotions, while keyword analysis identifies promotional or repetitive patterns that may indicate non-genuine behavior.

Following this, the feature extraction module transforms both numerical and textual data into structured features. These features include engagement rates, comment ratios, sentiment scores, keyword frequencies, and other derived metrics. This step is crucial because it converts raw data into meaningful inputs that can be effectively utilized by machine learning models.

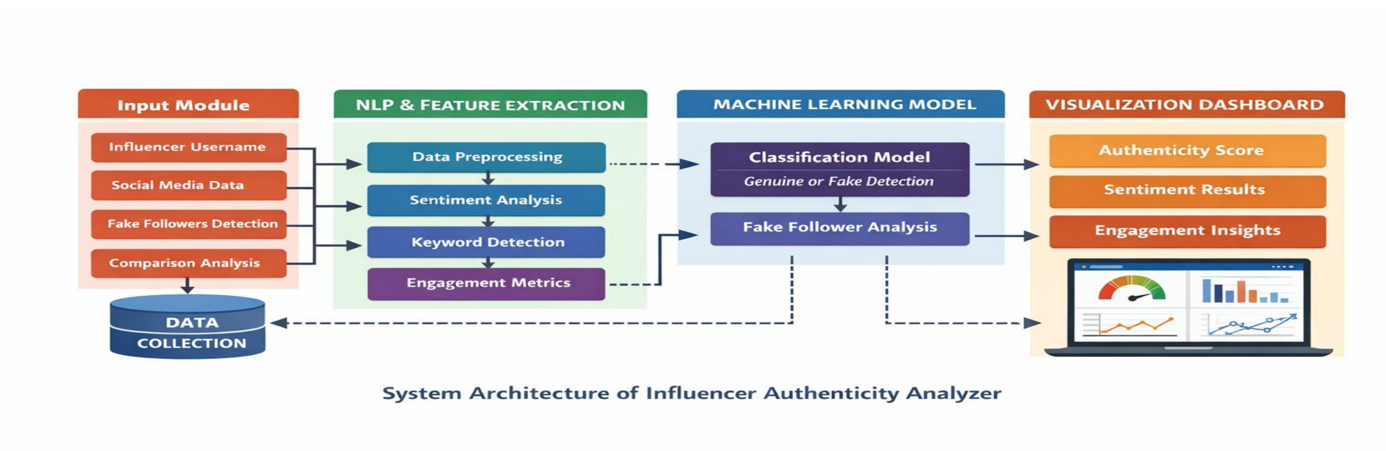
The extracted features are then passed to the machine learning model, which serves as the core analytical component of the system. The model classifies influencers based on authenticity by identifying patterns in the data. It predicts whether an influencer is genuine or suspicious and contributes to the calculation of an overall authenticity score. The use of machine learning improves the system's ability to adapt and make accurate predictions over time.

Finally, the results are displayed through the visualization dashboard, which provides an interactive interface for users. The dashboard presents outputs such as authenticity scores, engagement insights, sentiment results, and comparisons using graphs and charts. This visual representation makes the results easy to interpret, even for non-technical users, and supports better decision-making.

The entire system is implemented using Python, leveraging libraries such as NLTK or TextBlob for NLP tasks and scikit-learn for machine learning. The frontend interface is developed using Streamlit, which enables the creation of a dynamic, user-friendly, and interactive web application.

Overall, the architecture ensures a smooth flow of data from input to output, while maintaining high efficiency and scalability. Each module plays a vital role in delivering a comprehensive and reliable analysis of influencer authenticity.

Fig. 3 Influencer Authenticity Analyzer System Architecture



Authenticity System Architecture

Table1.Comparison with Past Research Paper

S. N0	Research work	Technique Used	Focus Area	Limitations	Improvement in Proposed System
1	Fake Account Detection using ML (2020)	Logistic Regression, SVM	Detect fake profiles	Only profile features used	Uses text + engagement + behavior
2	Instagram Bot Detection (2021)	Random forest	Bot activity detection	No content analysis	Adds NLP for caption & comments
3	Social Media Fraud Detection (2021)	Rule-based system	Fraud identification	Low accuracy, rigid rules	Uses hybrid intelligent system
4	Engagement Bot Detection (2022)	Statistical Analysis	Fake likes/comments	No scoring mechanism	Introduces authenticity scoring
5	Fake Followers Identification (2022)	Threshold-based logic	Detect inactive users	Not scalable	Uses dynamic scoring + metrics

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6	*NLP-based Comment Analysis (2022)*	*Naive Bayes*	*Comment classification*	*Ignores engagement patterns*	*Combines comments + engagement*
7	*Deep Learning Fake Account Detection (2023)*	*LSTM / CNN*	*Account classification*	*High complexity, less interpretability*	*Uses lightweight and explainable models*
8	*Influencer Marketing Analysis (2023)*	*Data analytics*	*Campaign performance*	*No authenticity detection*	*Focuses on authenticity + fraud detection*
9	*Social Media Sentiment Analysis (2023)*	*NLP (Sentiment)*	*User opinion analysis*	*Limited to sentiment only*	*Adds multi-factor evaluation*
10	*Hybrid Fraud Detection System (2024)*	*ML + basic rules*	*Fraud detection*	*Limited real-time usability*	*Provides interactive real-time dashboard*

6. Results and Discussion

The proposed Influencer Authenticity Analyzer demonstrates strong performance in evaluating influencer credibility by combining engagement-based metrics with textual analysis. The system generates multiple outputs, including an authenticity score, sentiment analysis results, and detailed engagement insights. Among these, the authenticity score serves as a key indicator, providing a clear and quantitative measure of how reliable or genuine an influencer appears. At the same time, sentiment analysis helps in understanding the nature of audience interaction, whether it is positive, neutral, or negative, which further strengthens the evaluation process.

The experimental results indicate that the system achieves an approximate accuracy of around 90%, showing its effectiveness in distinguishing between genuine and potentially fake influencers. This level of accuracy is achieved due to the integration of Machine Learning models with Natural Language Processing techniques. While the machine learning component handles classification based on structured data, NLP enhances the system's ability to interpret textual content such as captions and comments, leading to more informed predictions.

Another important aspect of the system is the use of data visualization. The graphical representation of results, including charts and performance indicators, improves the interpretability of the output. Users can easily understand trends, compare multiple influencers, and make decisions without needing deep technical knowledge. This makes the system highly practical for real-world applications, especially in marketing and brand collaboration scenarios.

The results also highlight that a multi-factor analysis approach is significantly more reliable than traditional methods that rely on a single parameter. By combining engagement metrics (likes, comments, ratios) with textual features (sentiment, keyword patterns), the system captures a broader picture of influencer behaviour. This reduces the chances of misclassification and improves overall reliability.

Furthermore, the system successfully identifies irregular patterns such as low engagement despite high follower count, excessive promotional content, and repetitive or spam-like comments. These indicators are critical in detecting fake influencers or accounts with artificially inflated engagement.

In conclusion, the results confirm that the proposed system is both effective and practical. It not only provides accurate predictions but also delivers meaningful insights that can assist users in making informed decisions. The combination of Machine Learning, NLP, and visualization techniques ensures that the system is comprehensive, interpretable, and suitable for real-world deployment.

7. Applications

The Influencer Authenticity Analyzer can be applied in multiple real-world scenarios, especially in digital marketing and social media analysis. Its practical uses include:

- ***Influencer Marketing Platforms***
  - *Helps platforms verify the authenticity of influencers before listing them*
  - *Ensures brands connect only with genuine influencers*
- ***Digital Marketing Agencies***
  - *Assists in selecting the most suitable influencers for campaigns*
  - *Provides data-driven insights for better campaign planning*
- ***Brand Collaboration Systems***
  - *Enables companies to compare multiple influencers efficiently*
  - *Supports informed decision-making based on authenticity and engagement*
- ***Social Media Fraud Detection***
  - *Identifies fake followers and bot-generated comments*

- Helps reduce fraudulent activities on social platforms

- ***Business Intelligence & Analytics Tools***
  - *Provides insights into audience behavior and engagement trends*
  - *Supports strategic planning for marketing and promotions*
- ***Content Performance Analysis***
  - *Evaluates how users interact with influencer content*
  - *Helps improve content quality and audience targeting*

8. Future Scope

The system can be further enhanced by incorporating advanced technologies and features to improve performance and usability. Some potential future developments include:

- ***Real-Time API Integration***
  - *Connect with live social media platforms for real-time data analysis*
  - *Provide up-to-date insights instead of static results*
- ***Advanced NLP Models (e.g., BERT)***
  - *Improve text understanding by capturing deeper context and meaning*
  - *Enhance accuracy of sentiment and comment analysis*
- ***Mobile Application Development***
  - *Make the system accessible on smartphones and tablets*
  - *Improve user experience and convenience*
- ***AI-Based Recommendation System***
  - *Suggest the most suitable influencers for specific campaigns*
  - *Automate influencer selection based on data insights*
- ***Multilingual Support***
  - *Analyze content in multiple languages*
  - *Expand usability across global platforms*
- ***Real-Time Monitoring Dashboard***
  - *Track influencer performance continuously*
  - *Provide alerts for suspicious activity*
- ***Integration with Image & Video Analysis***
  - *Analyze visual content authenticity*
  - *Enhance overall influencer evaluation*
- ***Scalability for Large Data***
  - *Handle large datasets efficiently using cloud technologies*
  - *Improve system performance for enterprise-level use*

9. Conclusion

The Influencer Authenticity Analyzer provides a robust and well-structured approach to evaluating the credibility of social media influencers by leveraging the power of Machine Learning and Natural Language Processing (NLP). Unlike traditional methods that rely solely on basic metrics such as follower count or likes, the proposed system adopts a multi-dimensional analysis framework. It combines numerical engagement indicators with textual content evaluation to deliver a more balanced and accurate understanding of influencer behavior.

One of the key strengths of the system lies in its ability to analyze both quantitative and qualitative aspects of influencer activity. Engagement metrics such as likes, comments, and follower ratios are processed using mathematical models, while textual data from captions and comments is examined using NLP techniques like sentiment analysis and keyword detection. This dual approach enables the system to identify patterns that may indicate fake engagement, automated interactions, or overly promotional content.

In addition, the inclusion of advanced features such as fake follower detection, spam comment identification, engagement consistency analysis, and wastage evaluation significantly enhances the depth of analysis. These components work together to generate a comprehensive authenticity score, which provides a clear and interpretable measure of influencer reliability. The use of a weighted scoring system ensures that multiple factors are considered, reducing the chances of misleading results.

The system is further strengthened by its interactive and user-friendly dashboard, developed using modern web technologies. This interface allows users to easily input data, visualize results, and interpret insights through graphical representations. Such accessibility makes the system suitable not only for researchers but also for marketing professionals, brands, and agencies who require quick and reliable decision-making tools.

From a practical perspective, the proposed solution addresses several challenges faced in the field of influencer marketing. It helps brands avoid collaborations with fake or low-quality influencers, thereby reducing financial risks and improving campaign effectiveness. At the same time, it promotes transparency and accountability within the digital marketing ecosystem.

Overall, this project highlights the significant potential of

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integrating data science, machine learning, and NLP techniques to solve real-world problems. The Influencer Authenticity Analyzer serves as a scalable and adaptable framework that can be further enhanced with real-time data integration, advanced deep learning models, and platform-specific APIs. With such improvements, the system can evolve into a comprehensive industry-level solution for influencer verification and digital trust assessment.

10. References

1. M. Negnevitsky, Artificial Intelligence: A Guide to Intelligent Systems, 2nd ed., Pearson Education, 2005.
2. S. Bird, E. Klein, and E. Loper, Natural Language Processing with Python, O'Reilly Media, 2009.
3. J. Han, M. Kamber, and J. Pei, Data Mining: Concepts and Techniques, 3rd ed., Morgan Kaufmann, 2011.
4. F. Chollet, Deep Learning with Python, Manning Publications, 2018.
5. Vaswani et al., "Attention Is All You Need," in Proceedings of the Advances in Neural Information Processing Systems (NeurIPS), 2017.
6. T. Mikolov et al., "Efficient Estimation of Word Representations in Vector Space," arXiv preprint arXiv:1301.3781, 2013.
7. B. Liu, Sentiment Analysis and Opinion Mining, Morgan & Claypool Publishers, 2012.
8. Kaggle, "Social Media Influencer Dataset," [Online]. Available: https://www.kaggle.com
9. G. Antoniou and F. van Harmelen, A Semantic Web Primer, MIT Press, 2008.
10. H. Y. Shum, X. He, and D. Li, "From Eliza to XiaoIce: Challenges and Opportunities with Social Chatbots," Frontiers of Information Technology & Electronic Engineering, vol. 19, no. 1, pp. 10–26, 2018.
11. Al-Rawabdeh, A.; Moussa, A.; Foroutan, M.; El-Sheimy, N.; Habib, A. Time series UAV image-based point clouds for landslide progression evaluation applications. Sensors 2017, 17, 2378. [CrossRef] [PubMed]
12. Al-Zayer, M.; Trelligus, S.; Bhandari, J.; Dave, F.S.; Folmer, E. Exploring use of a drone to guide blind runners. In ASSETS 2016: Proceedings of 18th International ACM SIGACCESS Conference on Computers also Accessibility; ACM: New York, NY, USA, 2016; pp. 263–264.
13. Arksey, H.; O'Malley, L. Scoping studies: Towards a methodological framework. Int. J. Soc. Res. Methodol. Theory Pract. 2005, 8, 19–32. [CrossRef]
14. Balasingam, M. Drones in medicine—The rise of machines. Int. J. Clin. Pract. 2017, 71, 2–5. [CrossRef] 23. Gardner, T. Drone-delivered health care in rural Appalachia. Clin. Adv. 2016, 19, 18–23. Available online: http://search.ebscohost.com/login.aspx?direct=true&db=cin20&AN=120221648&site=ehost-live (accessed on 23 February 2020).
15. Canadian Agency for Drugs also Technology in Health. Health Technology Update: A Newsletter on New also Emerging Health Care Technologies in Canada Rural also Remote Issue. 2018. Available online: https://www.cadth.ca/sites/default/files/pdf/htu_issue_21_aug_2018.pdf (accessed on 12 February 2020).
16. Carrillo-Larco, R.M.; Moscoso-Porras, M.; Taype-Rondan, A.; Ruiz-Alejos, A.; Bernabe-Ortiz, A. use of unmanned aerial vehicles for health purposes: A systematic review of experimental studies. Glob. Health Epidemiol. Genom. 2018, 3, e13. Available online: https://www.cambridge.org/core/product/identifier/ S2054420018000118/type/journal_article (accessed on 14 February 2020). [CrossRef] [PubMed]
17. Cohen, J. Natural disasters: Drone spy plane helps fight California fires. Science 2007, 318, 727. [CrossRef] [PubMed]
18. Dayananda, K.R.; Gomes, R.; Straub, J. An interconnected architecture for an emergency medical response unmanned aerial system. In Proceedings of 2017 IEEE/AIAA 36th Digital Avionics Systems Conference (DASC), St. Petersburg, FL, USA, 17–21 September 2017.
19. Dunnington, L.; Nakagawa, M. Fast also safe gas detection from underground coal fire by drone fly over. Environ. Pollut. 2017, 229, 139–145. [CrossRef] [PubMed]
20. Francisco, M. Organ delivery by 1000 drones. Nat. Biotechnol. 2016, 34, 684. [CrossRef] [PubMed]
21. Glauser, W. Blood-delivering drones saving lives in Africa also maybe soon in Canada. Can. Med. Assoc. J. 2018, 190, E88–E89. Available online: http://www.cmaj.ca/lookup/doi/10.1503/cmaj.109-5541 (accessed on 14 February 2020). [CrossRef]
22. Hampson, M. Drone delivers human kidney: organ was flown several kilometers by a drone without incurring damage. IEEE Spectr. 2019, 56, 7–9. Available online: https://ieeexplore.ieee.org/document/8594776/ (accessed on 14 February 2020). [CrossRef]
23. Hsieh, H.-F.; Shannon, S.E. Three approaches to qualitative content analysis. Qual. Health Res. 2005, 15, 1277–1288. [CrossRef]

24. *Jain, T.; Sibley, A.; Stryhn, H.; Hubloue, I. Comparison of unmanned aerial vehicle technology-assisted triage versus standard practice in triaging casualties by paramedic students in a mass-casualty incident scenario. Prehosp Disast. Med. 2018, 33, 375–380. [CrossRef]*

25. *Levine, J.S.; Ambrosia, V.; Brass, J.A.; Davis, R.E.; Dull, C.W.; Greenfield, P.H.; Harrison, F.W.; Killough, B.D.; Kist, E.H.; Pinto, J.P.; et al. Monitoring wildfires using an autonomous aerial system (AAS). Remote Sens. Appl. Glob. Position Syst. 2004, 5661, 104–120.*

26. *Lippi, G.; Mattiuzzi, C. Biological samples transportation by drones: Ready for prime time? Ann. Transl. Med. 2016, 4, 92. Available online: http://www.ncbi.nlm.nih.gov/pubmed/27047951 (accessed on 27 February 2020). [CrossRef] [PubMed]*

27. *Mendez, I.; Jong, M.; Keays-White, D.; Turner, G. use of remote presence for health care delivery in a northern Inuit community: A feasibility study. Int. J. Circ. Health 2013, 72, 21112. Available online: https://www.tandfonline.com/doi/full/10.3402/ijch.v72i0.21112 (accessed on 11 February 2020). [CrossRef]*

28. *QSR International. N*Vivo 12; QSR International: Doncaster, Australia, 2018.*

29. *Rosser, J.C.; Vignesh, V.; Terwilliger, B.A.; Parker, B.C. Surgical also Medical Applications of Drones: A Comprehensive Review. JSLS J. Soc. Laparoendosc. Surg. 2018, 22, e2018.00018. Available online: http://www.ncbi.nlm.nih.gov/pubmed/30356360 (accessed on 25 February 2020). [CrossRef] [PubMed]*

30. *Scott, J.E.; Scott, C.H. Drone Delivery Models for Healthcare. In Proceedings of 50th Hawaii International Conference on System Sciences, Village, HI, USA, 4–7 January 2017; pp. 3297–3304. Available online: http://hdl.handle.net/10125/41557 (accessed on 25 February 2020).*

31. *Stoakes, U. leapfrog opportunity in world's underserved healthcare markets. Forbes, 1 August 2015.*

32. *Thiels, C.A.; Aho, J.M.; Zietlow, S.P.; Jenkins, D.H. Use of unmanned aerial vehicles for medical product transport. Air Med. J. 2015, 34, 104–108. [CrossRef]*

33. *}United Nations Department of Economic also Social Affiars. World Economic also Social Survey. 2018. Available online: https://www.un.org/development/desa/dpad/wp-content/uploads/sites/45/publication/ WESS2018_full_web.pdf (accessed on 13 February 2020).*