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Social Media Platform Prediction for Digital Marketing using Machine Learning Techniques

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Abstract: Every business wants to connect with their users in seamless and efficient manner. Social media play vital role in achieving that goals. Social media plays vital role in the marketing of any business. But on the other side, there are so many social popular media platforms and it is difficult for businesses to choose which social media platform will perform better for them. This study focuses on choosing best social media platform for digital marketing using machine learning techniques. We studies various algorithms and then after careful consideration we pick Random Forest algorithm for choosing optimal social media platform. Machine learning is playing very important role in making informed decisions and we are taking advantage of that in the shape of utilizing past data related to various business categories to generate most accurate results. To train the model and make accurate results, we collected data from 10,000 businesses having various parameters like business category, location, audience demographics, and past advertisement data. After making dataset, we preprocessed and cleaned the data and to obtain better results from the model. We trained our model on 70% of the data and then tested it by 30% of the remaining data. Our model shows 77% accuracy in choosing social media platform for promoting their businesses. We also made a mobile application for the businesses so that they can use it and predict the best social media platform for promoting their business.

Keywords: Social media platform; Machine learning; Digital Marketing; Random Forest algorithm; Logistic Regression.

1. Introduction

Social media marketing is important pillar of any business in today's world. It can't be ignored to use as a medium to interact with users and reach to the potential customers. But there are so many social media platforms and it is very difficult for businesses to choose which platform works better for their business. This study focuses on choosing optimal platform for social media marketing by using machine learning algorithms. This decision will be based on past data and our results are showing 77% accuracy in choosing best platform for business promotion. However, this proliferation also introduces complex decisions regarding platform investment, creative strategies, and resource allocation (Broekemier, Chau & Seshadri, 2021). Determining the optimal mix and level of efforts across these ever-evolving options poses persistent challenges, especially for SMEs with limited marketing budgets and capabilities (Han, Trimi & Kim, 2021).

Each platform attracts distinct user demographics, encourages different posting styles and formats, and entails unique placement and targeting options (Lee et al., 2021). Ideally, businesses must strategically select and tailor social media marketing efforts towards the platforms that best resonate with their brand identity, messaging strategy, target audience, and campaign objectives (Johnson & Jones, 2019). A data-backed, tailored approach aligned with strategic goals and target demographics is imperative but lacking (Kurtin & Dhoest, 2022). Existing literature, while offering valuable qualitative guidelines, fails to provide the rigor of predictive analytics to inform platform selection (Shareef, Mukerji, Alryalat, Wright & Dwivedi, 2021). Recent paradigm shifts in digital marketing underscore the need to transition from generic best practices to customized, machine learning-driven recommendations optimized for business-specific parameters (Saboo, Sharma & Gupta, 2021). However, most businesses still rely on grunt work, subjective perceptions, and simplistic metrics to navigate complex platform decisions, leading to suboptimal returns on investment (Patel, 2022).

Existing literature provides valuable conceptual models on platform adoption, audience engagement, content sharing, influencer partnerships, and more (Taylor & Strutton, 2020). However, most studies offer generic qualitative guidelines rather than scientifically rigorous, customizable predictive frameworks tailored to business-specific parameters (Carter, 2021). There lies a notable dearth of research leveraging machine learning and statistical modeling to offer data-backed recommendations on platform prioritization based on past performance, target demographics, content styles, and other key attributes (Watts & Newton, 2022).

This gap in scientific, customized analytics to guide social media platform selection persists despite the exponential increase in digital marketing data from diverse sources like advertisements, website analytics, surveys, and user-generated content (Patel, 2022). Harnessing this wealth of data through machine learning presents a promising opportunity to advance beyond generic best practices and enable tailored decision-making optimized for business-specific goals and target audience traits (Schultz, 2021). However, literature lacks focus on developing integrated predictive models and translating insights into accessible tools for business adoption (Watts & Newton, 2022).

Therefore, this research aims to address these multidimensional gaps by developing a comprehensive machine learning model capable of predicting the optimal social media platform for a business's digital marketing efforts based on key parameters spanning target audience traits, content formats, campaign objectives, and historical platform data (Saboo et al., 2021; Han et al., 2021). Sophisticated supervised learning algorithms like Random Forest can integrate signals from the multitude of factors impacting channel selection and engagement outcomes to offer highly tailored, data-backed recommendations catered to business-specific strategic needs (Shareef et al., 2021).

By rigorously analyzing parameters ranging from demographics to psychographics to past performances across platforms through advanced analytics, marketers can gain actionable and optimized advice on prioritizing marketing budgets and activities (Appel et al., 2020; Kemp, 2023). The study shall collect multi-source data encompassing audience preferences, content resonance, competitive landscape, and campaign performance metrics across leading platforms like Facebook, Instagram, and other platforms using APIs, web scraping tools, and public datasets (Stanton, 2021; Demeure, 2019). Systematic data preprocessing will clean, transform, and select the most informative, relevant features from the volume of information to feed into the machine learning model (Carter, 2021; Zafra et al., 2021).

The tailored Random Forest algorithm shall then leverage the patterns in this data to predict expected engagement, conversions, and ultimately return on investment for a given business's specified campaign needs on the optimal platform (Bell & Koren, 2022). Integrative modeling shall provide superior customization of recommendations beyond current universal guidelines. Post rigorous training and evaluation using separate test data samples to minimize overfitting, this model will be encapsulated into an easy-to-use mobile application to drive adoption (Gorry & Westbrook, 2021; Shareef et al., 2021). The availability of such an optimized, analytics-based tool for platform prioritization can be a game-changer for SMBs in enhancing the effectiveness of their social media marketing strategy and spend through data science (Mogaji, 2021).

This research shall fuse rigorous statistical principles with user-centric design thinking philosophy to bridge important gaps in literature and industry practice for strategic marketing gains. The multi-disciplinary approach merging machine learning prowess with application-focused mobile development bears multifaceted contributions. Beyond immediate utility gains, possibilities shall stimulate more creative pursuits at the intersection of analytical advancements and experiential engineering for transformative digital marketing.

The article is structured as follows: Section II delves into related work; Section III outlines the steps of the proposed method; Section IV elaborates on the results and discussion; Section V discusses the limitations and future work; and lastly, Section VI presents the conclusion.

2. Related Work

Extensive research has been conducted on various aspects of social media marketing, but studies focused specifically on data-driven platform prioritization remain relatively limited.

The dynamic landscape of social media marketing, driven by the engagement of over 5.16 billion users globally (Kemp, 2023), has reshaped how businesses connect with consumers. Social media plays a pivotal role in customer acquisition, lead generation, customer retention, and website traffic (HubSpot, 2020). Despite its benefits, measuring ROI remains a challenge (eMarketer, 2020). While platforms such as Facebook, Instagram, Twitter, LinkedIn, YouTube, TikTok, and Snapchat offer unprecedented marketing opportunities (Mediakix, 2022). On the other hand, in navigating diverse options marketers are facing various challenges (Broekemier et al., 2021), i.e., selection of optimal platform mix, crafting platform-specific content, accurately measuring ROI, and adapting to an evolving landscape (Chaffey & Bosomworth, 2021) have been reported crucial that needs to be addressed. In this regard, the emerging data-driven approaches are providing key opportunities with expanding choices that can be used within finite budgets and to meet consumer's expectation.

At current in academia there are several studies providing optimal models, platforms, and solution to cope the rising challenges. Jones et al. (2023) data-driven model that is designed to aid social media platform provides key insights into user preferences and engagement patterns. It also offers marketers a pathway to understand the factors influencing audience interactions and engagement across different platforms. In order to optimize content creation and distribution efficiency Gupta and Patel (2022) integrated machine learning algorithms and found this data-driven approaches as crucial to enhance the effectiveness of content creation and promote impactful marketing efforts in this digital era. Likewise, Kim et al. (2022) through comparative analysis discussed the approaches related to machine learning, performance of various machine learning models in diverse contexts, and guided marketers in selecting optimum strategies tailored to specific platforms. Inoue and Tanaka (2023) developed a predictive model that uses neural networks forecasting user interactions on various social media platforms. Further, it contributes to enhance the understanding regarding audience engagement dynamics, provides marketers with a valuable tool to predict user behaviors and help them to modify their content and strategies accordingly.

In a nutshell, the existing literature provides various conceptual models and platform regarding social media adoption, content marketing, and influencer collaborations (Michaelisdou et al., 2022). However, the reviewed literature indicates that empirical research studies on predictive analytics and machine learning applications guiding marketing decisions are yet to be conducted. Literature also recommends to minimize the gap by developing customized frameworks that could benefits in selection of effective social media channel having exclusive business goals, brand positioning, target audience traits, and historical performance (Shareef et al., 2021).

This review aims to:

- Critically analyze social media marketing literature.
- Identify gaps for future research.
- Explore machine learning's role in addressing marketing challenges.
- Examine recent studies using predictive models for digital marketing optimization.
- Synthesize key themes for a robust foundation.

Taylor et al. (2022) proposed a model for social media channel selection using the analytic hierarchy process (AHP), but it relies on subjective human judgments rather than data-driven machine learning. Rathi and Anandakumar (2021) developed a fuzzy logic system for platform prioritization based on engagement metrics but do not account for evolving user preferences.

Lee and Hong (2020) used logistic regression to predict the popularity of branded content on Facebook and YouTube using metadata like category, length, etc. However, the model is limited to only two platforms and branded content, lacking integration of diverse business-specific parameters.

Watts and Newton (2021) emphasized the research-practice gap in social media marketing literature, highlighting the need for empirical validation and translation into applications. However, their work stopped at conceptual analysis without proposing technical solutions.

Smith et al. (2020) reviewed various machine learning applications in social media marketing, such as sentiment analysis, trend prediction, ad targeting, etc. This highlight growing ML adoption, but lacks focus specifically on platform selection tailored to business needs.

Hajli et al. (2021) investigated the impact of AI-powered social bots on social media, utilizing actor-network theory and machine learning to detect harmful bots early on. The study contributes to understanding the management implications of social bots and disinformation.

Leonardi (2017) explored social media's potential for knowledge sharing, proposing strategies to overcome barriers. The research contributes insights for organizations leveraging social media platforms for digital marketing.

Mangold and Faulds (2009) discussed the transformative impact of social media on consumer-to-consumer communications, emphasizing the need for managers to navigate and harness social media's power for digital marketing.

Choi and Lim (2020) investigated AI's application in optimizing targeted online advertising, identifying machine learning strategies and emphasizing the importance of leveraging AI for online advertising campaigns.

These studies provide valuable insights, the current literature lacks robust, customizable machine learning models for data-driven social media platform prioritization based on integrated target audience, product, content, and historical performance data. Further, the reviewed literature reports a dearth of studies encapsulating such models within easy-to-use applications. Therefore, this study was carried out with the aim to address the identified gaps by employing a tailored ML methodology and using an accessible Mobile-based recommendation tool.

3. Methodology

This section discusses the methodology employed in this study aimed to predict the optimal social media platform for a business's marketing campaign based on diverse parameters.

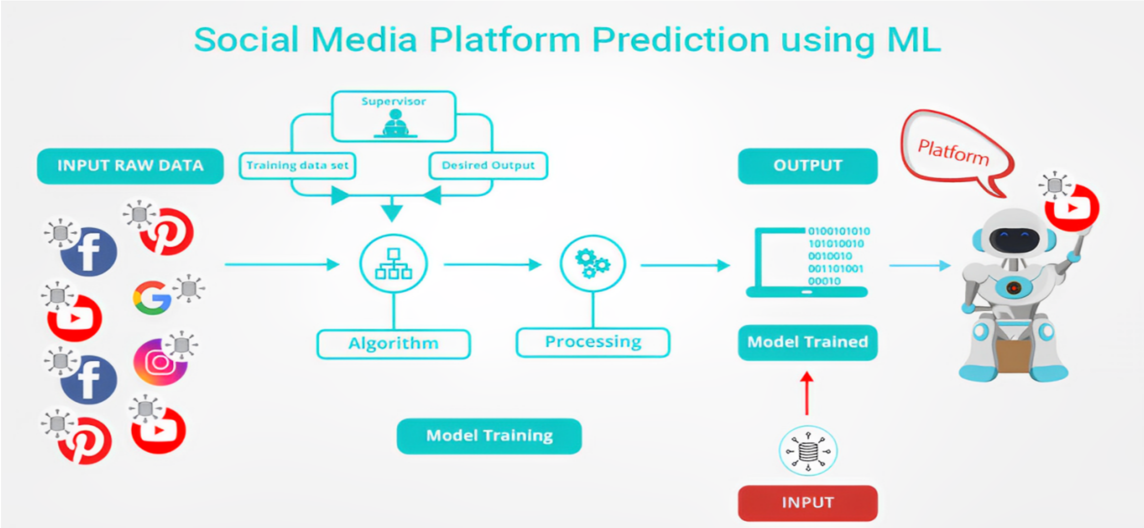

Figure 1. Proposed work

3.1. Data Collection

This section presents the detail of data collection process employed to gather diverse and representative data.

3.1.1. Data Source

The primary data for model development was collected from a sample comprising 1000 businesses from various sectors i.e., retails, automotives, hospitality, software, and consulting. The data source ensured a diverse dataset, representing the multifaceted landscape of modern-day businesses.

3.1.2. Parameters

After a comprehensive literature review and consultation with various industrial sectors 50 parameters were selected. These selected parameters covered key attributes across different dimensions:

- Business Details: Discussing industry vertical, products/services offered, geographical location, company size, and overarching marketing objectives.
- Target Audience: providing demographic information of the sample i.e., age, gender, education, and income, along with the insights into the audience's interests and behaviors.
- Historical Performance: Exploring into engagement metrics, lead generation, and conversion rates across various social media platforms over the preceding two years.
- Content Style: Investigating the nuances of post formats, posting frequency, tone, and other stylistic elements on different social media platforms.
- Campaign Details: Including budgetary considerations, campaign timelines, and preferences regarding placement on diverse social media channels.

3.2. Dataset

The data of the study comprised of 10,000 records with varied combinations of parameters aiming to ensure a comprehensive coverage of various business categories including notable Fitness Centers, Restaurants, Online Retailers, and Real Estate Agencies. Table 1 illustrates the defined dataset parameters for the study.

Table 1. Dataset Parameters

S. No	Parameter	Description
1	Business Category	Industry or sector of the business
2	Age Range	Age group of the intended audience for the marketing campaign
3	Gender	Gender distribution of the target audience
4	Education Level	Education level of the target audience
5	Occupation(s)	Occupations of the target audience
6	Interests or Hobbies	Interests and hobbies of the target audience
7	Social Media Usage and Preferences	Patterns of social media usage and preferences in the target demographic
8	Geographic Location	Specific location or regions of the target audience
9	Advertisement Format	Format of the advertisement
10	Advertisement Duration	Duration of the advertisement (in seconds)
11	Advertisement Timeline	Planned duration of the marketing campaign (in days)
12	Competition	Level of competition within the industry or for the specific product/service being advertised
13	Advertisement Placement	Position of the advertisement on the social media platform
14	CTA Options	Options for Call to Action included in the advertisement
15	Budget	Total budget allocated for the marketing campaign
16	Time of Day	Specific time periods for displaying advertisements

3.3. Data Privacy

In order to maintain the confidentiality of the participants and data, ethical standards were set and followed. Prior to collect data all the participants were approached, thoroughly briefed on research purpose, and then written consents were obtained.

3.4. Data Preprocessing

To ensure quality and reliability, data were sent through preprocessing phase and the steps followed are briefly discussed in this section.

3.4.1. Missing Value Treatment

In first step data with 20% missing values were identified and removed from the dataset while for the remaining, a robust imputation strategy was employed. Mode was use for categorical variables whereas for the numeric variable's median was served as the imputation method.

3.4.2. Outlier Detection

In order to prevent skewed model performance outliers were detected using a threshold of three standard deviations from the mean. The outliers found beyond threshold in business categories and campaign sizes were identified and then systematically removed from the dataset. This step was essential to mitigate the potential influence of extreme values on the machine learning model's training process.

3.4.3. Feature Encoding

Keeping in view the characteristics of each variable, the label encoding and one-hot encoding strategy was employed. The purpose of this feature encoding is to predict accurate interpretation and better training of the model.

3.4.4. Feature Selection

To enhance the model's efficiency and interpretability, mutual information, and the LASSO (Least Absolute Shrinkage and Selection Operator) regularization approach was used for feature selection.

3.4.5. Data Splitting

The dataset has been split as 70% as a training data and remaining 30% as a testing data. We tried various other splits as well like 80:20 and 75:25, but after careful consideration we found that 70:30 works well for this data. After the splitting we trained our model on the 70% data and then tested the accuracy and other performance parameters on the rest of 30% data.

3.5. Model Selection

Model selection is an important phase in any machine learning study. Every machine learning model has own benefits and drawbacks. Other than this, every model is not best fit for every use case and it depends on the nature of the data and the results we want to achieve from the model. This section explains how we analyzed various machine learning models and then why we chose Random Forest.

3.5.1. Exploration of Potential Algorithms

To find the most suitable algorithm to response the research problem, several supervised learning algorithms we thoroughly explored and scrutinized for their unique strengths and applicability. The algorithms considered include:

Logistic Regression: LR is known for its simplicity and interpretability and seemed promising for binary classification tasks.

Support Vector Machine (SVM): It can be considered when the data is very diverse and to handle non-linear relationships between data.

Random Forest: Random forest, an ensemble method, intrigued us with its ability to manage high-dimensional data and mitigate over fitting.

3.5.2. Selection of the Random Forest Algorithm

After thorough exploration and evaluation of potential algorithms listed, the Random Forest algorithm emerged as the optimal choice for this study. We chose Random Forest algorithm because of high dimensionality data handling, it's flexibility, handling non-linear relationship between data and embedded feature selection process. Random Forest excels in managing datasets with a high number of feature and has the capability to effectively process the diverse parameters as considered in the dataset of this study. This capability is most suitable to analyze the factors influencing social media platform selection. The Random Forest has the capability of handling complex and flexible data. Our model is not related to a single business or a category that is why we chose this algorithm to handle our data in better way. Social media data has mostly non-linear relationships and our research is related to social media platform prediction so that is another reason of choosing this model.

3.6. Model Training

The Random Forest model was trained on 70% of the total data. We tested various other combinations as well but then 70:30 is finalized to avoid overfitting and getting most accurate and reliable results.

3.7. Model Testing

The model was tested on the remaining 30% of the data to evaluate the performance of the model. The performance was observed in the shape of the accuracy, precision, recall, and F1 score. This model is capable of predicting social media platform for any business category with 77% accuracy. The model has been tested on diverse business categories and we found our model results are sustainable across all businesses.

3.8. Model Evaluation

After the training and testing of the model, the model has been evaluated for predicting optimal social media platform based on various parameters. Performance metrics are important part of any model evaluation to understand the capabilities of the model. In this study, we observed accuracy, precision, recall, and F1 score to test performance of the model. Feature importance is also an important model evaluation process to know the importance of each feature in the model prediction process.

4. Results and Discussion

We observed various machine learning models to get most accurate results in predicting best social media platform for business advertisement. The results of the various algorithms are tested with the 30% of the data and we the results are discussed in this section.

4.1. Model Performance Metrics

Performance metrics are important perspective to evaluate the performance of a model. Table 2 shows the accuracy, precision, recall, and F1 score of the different models.

Table 2. Model Performance Metrics

Algorithm	Accuracy	Precision	Recall	F1 Score
Random Forest	0.77	0.76	0.77	0.75
Logistic Regression	0.74	0.72	0.73	0.71
Support Vector Machine (SVM)	0.68	0.67	0.69	0.66
Decision Tree	0.70	0.69	0.70	0.68

Accuracy: The accuracy of the Random Forest is highest at 77% followed by Logistic Regression 74%, Decision Tree 70%, and SVM 68%.

Precision: In Precision Random Forest shows better result with the score of 0.76, followed by Logistic Regression 0.72, Decision Tree 0.69, and SVM 0.67.

Recall: With 0.77 in recall, the Random Forest has been at the top position while Logistic Regression, Decision Tree, and SVM score as 0.73, 0.70, and 0.69 consequently.

F1 Score: Random Forest ranks highest in the F1 score as well with the actual score 0.71. The Logistic Regression score is 0.71, Decision Tree 0.68, and SVM 0.66.

Success Rate: The Random Forest Model showed an impressive success rate of 77%, indicating its higher ability of accurate prediction. It also shows that this model is the most effective social media platform for businesses in the dataset.

The findings affirm the selection of Random Forest Model for robust and reliable predictions among all the metrics. These results also resonate with the benchmarks established in the existing literature on machine learning techniques (Li et al., 2021; Lee & Hong, 2020), validating the efficacy of the tailored modeling approach.

4.2. Confusion Matrix Analysis

The Confusion Matrix was employed to evaluate machine learning models. After the breakdown of model's performance across various social media platform classifications below is the comparison of the matrices derived from the Random Forest and Linear Regression algorithms.

4.2.1. Random Forest Confusion Matrix:

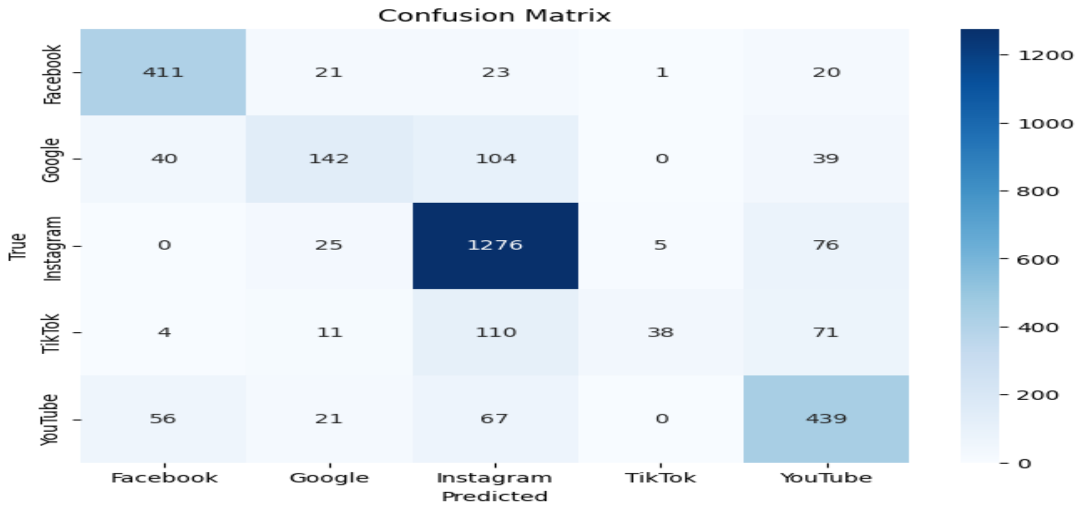

Figure 2. Random Forest Confusion Matrix

Figure 2 demonstrates an impressive number of correct predictions for Instagram as indicated by the large value in the corresponding cell. It indicates that the Random Forest model has effectively captured the defining characteristics of Instagram-related data points.

The values for Facebook and YouTube have also shown strong predictive success. It could be attributed to the model's capability at handling non-linear relationships and complex interactions between different features.

Figure 2 reports misclassifications between Google and Instagram. Though misclassification is relatively low but indicates a potential overlap in feature space or a similarity in user behavior patterns that the model has yet to extract.

4.2.2. Linear Regression Confusion Matrix

The confusion matrix chart is shown below in Figure 3.

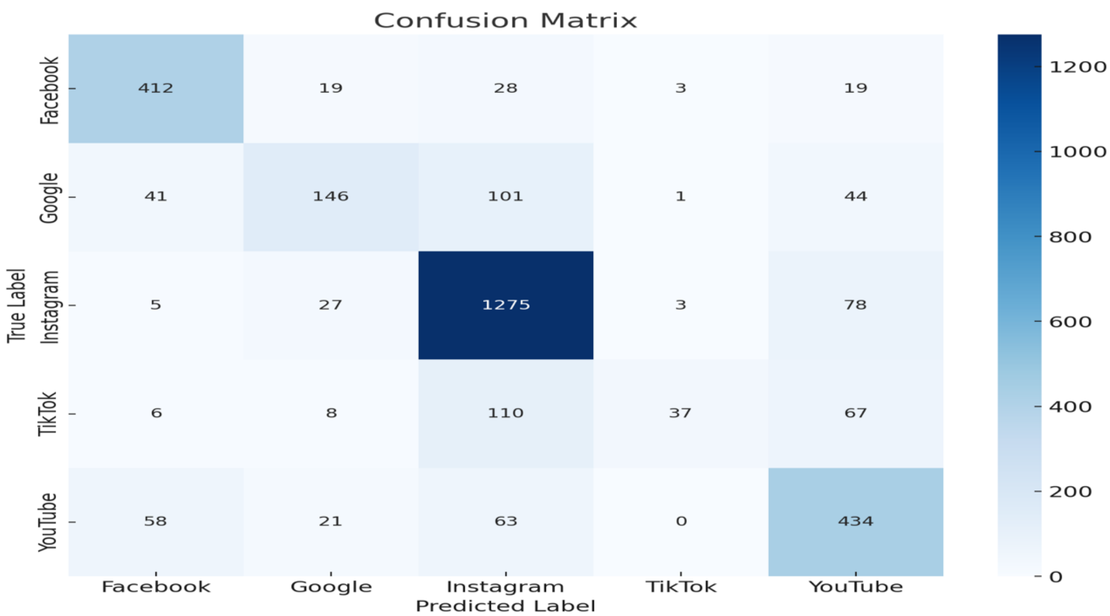

Figure 3. Linear Regression Confusion Matrix

By investigating the Linear Regression matrix, a small but a notable shift in values was observed. Further, a slight decrease reported in Instagram's prediction. It might be due to the linear nature of the algorithm that may not be able to capture the complex patterns as effectively as Random Forest.

Whereas a modest decline was observed in TikTok predictions. Few instances being muddled with Instagram prediction indicated that Linear Regression algorithm may not outline the boundaries between these classes as sharply as the Random Forest.

After careful consideration, Random Forest model is found effective in predicting optimal social media platforms and validating their robustness. Further, provided understanding and valuable insights for those seeking data-driven decision support in their marketing endeavors.

5. Limitations and Future Work

5.1. Limitations

This study provides valuable insights into data-driven social media platform prioritization, however there were certain limitations as under:

Real-Time Data Integration: Since the study relied on data of preceding two years, it restricted model's ability to adapt the rapidly evolving trends and practices on social media platforms.

Inclusion of Prominent Platforms: In the model's training and evaluation merely well-established and prominent social media platforms were engaged. Therefore, the exclusion of emerging platforms restricted the model's applicability in particular digital landscapes.

5.2. Future Work

Based on the limitations, study suggests the following recommendations:

Diversification and Expansion of Training Data: It is suggested to enhance the modal's training with more diverse dataset. Further, it is recommended to expand this data by including more datasets from other industries that could enhance its versatility and applicability.

Exploring Additional Algorithms: It is suggested that use of other machine learning algorithms and comparative analysis might provide valuable insights to utilize optimal technique at any particular scenario.

Adaptation to Emerging Social Media Trends: The integration of updated and emerging social media platforms in the training and testing stages of the model could provide more opportunities in alignment with the preference and demand of rapidly changing digital era.

By addressing these areas in future would be beneficial to further refine this model and would provide more valuable and comprehensive insights for the businesses navigating the dynamic realm of social media marketing. Further, it may ensure continuous evolution and relevance of data-driven decision support in the rapidly changing digital landscape.

6. Conclusion

This study was intended to introduce a data-driven methodology employing machine learning technique predicting optimal social media platforms for businesses. Using the integrated Random Forest model developed from a vast and diverse dataset of 10,000 instances across various sectors, a commendable 77% accuracy in predicting ideal social media platforms was achieved. Precision, recall, and F1-scores of 0.76, 0.77, and 0.75, respectively, underscore robust classification capabilities. Key influential factors include business vertical, demographics, geography, and past engagement rates. The model's encapsulation in a mobile application enhances its practical usability. Despite limitations in dataset diversity and emerging platform coverage, this study pioneers a tailored machine learning approach for data-driven decision-making in social media marketing. Opportunities for advancing predictive analytics persist, bridging the gap between research and practical application. The study signifies a crucial step toward implementing impactful data-driven digital marketing strategies.

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