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IMPACT OF SOCIAL MEDIA INTERACTIONS ON HUMAN SENTIMENTS: A MACHINE LEARNING APPROACH

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ABSTRACT

This research paper examines whether the interactions via social media have a positive or negative effect on human sentiments by closely examining through a sentiment analysis approach that involves machine learning. A set of 100 posts representing popular platforms like Twitter and Facebook were examined and categorized into positive, negative and neutral. It was found that the proverbial preponderance of negative feelings is a bit higher (40%) than both positive (35%) and neutral (25%) with the predisposition towards an open expression of dissatisfaction and concerns in the festival users. In order to categorize sentiments four models were utilized Logistic Regression, Support Vector Machine, Random Forest and Long Short-Term Memory (LSTM). Of these, LSTM had the highest accuracy (84%), which was better than the traditional ones in distinguishing contextual and sequential complexities of text. The correlation analysis revealed that positive and negative sentiments were correlated to a higher degree with engagement measures of likes, comments, and shares whereas neutral posts were comparatively less responded. Results of the importance analysis indicated that textual features played the most important role in sentiments prediction, especially the one based on TF-IDF and sentiment lexicon scores, with the role of engagement and user influence being less significant. Collectively, these results reflect the fact that machine learning can provide rigorous insights into the emotional expressions in cyberspace, showing the significance of online sentiment analysis on the communication in digital context and the behavior/social influence of users.

Keywords: Social Media, Human Sentiments, Sentiment Analysis, Machine Learning, Deep Learning, Engagement Metrics.

1. INTRODUCTION

In the digital age, the sphere of social media has become a strong tool in communications that breakdown geographic and cultural barriers and the way people communicate, speak out their views and share feelings. Social media platforms like Twitter, Facebook, and Instagram have emerged as vibrant platforms in the field of social debate and each like, comment, and share is representative of the opinion of users. Such sentiments, be they positive, negative, or neutral, not only reflect the subjects state of their emotions, but also affect the future of the masses and the general direction of action, opinion and even socio-political action. There is potential in the use of big data produced in millions of daily interactions, but it also poses a problem, because this unstructured and large-scale data is only interpretable with the use of advanced methods of computation. Since human sentiments are key to examining decision processes, consumer behavior and social influence, it has become arguably a relevant realm of study to examine how emotional expression has been altered by social media interaction.

Machine learning has the scalable and robust methodologies specifically to handle sentiment analysis, providing an opportunity to draw up patterns and classify sentiment over large amounts of data with high accuracy. Contrary to old-school linguistic or rule-based approaches, machine learning algorithms, including Logistic Regression, Support Vector Machines, Random Forests, and deep learning-based models of such as Long Short-Term Memory (LSTM) networks are capable of processing intricate language structure, contextual dependencies, and a variety of modes of expressing the language. The use of these methods to analyze social media content allows researchers not to only rank the emotions but also branch out into other implications such as the psychological impact of digital communication and the marketing implications and social effects. The paper thus attempts to explore how social media connects with or influences sentiments in human beings through machine learning and identify trends in sentiment switch by visualizing domain predictions, measure the performance of the classification model and the overall importance of sentiment analysis in the era of digital communication.

2. LITERATURE REVIEW

Al-Garadi et al. (2019) carried out the extensive survey of machine learning applications in predicting cyberbullying on social media in the age of big data. Their work identified advantages and deficits of the different algorithms, especially when working with non-structured text data in a large scale. They also indicated unresolved issues, like what they described as gift of imbalance and feature extraction complexities, and the potential necessity of real-time sentiment detection, a set of problems that formed the basis of future research on sentiment and social media analysis.

Alsayat (2022) examined the enhancement of sentiment analysis of social media applications based on an ensemble language model using deep learning. The work illustrated that using a combination of deep learning models increased the accuracy of classification with regard to the traditional approaches where there is one model alone. Through eliminating semantic ambiguity and context-sensitivity in a linguistic framework, the study of sentiment patterns in user-generated content was made more robust in a more generalized way.

Bangyal et al. (2021) evaluated the fake news detection in the context of the COVID-19 pandemic through deep learning-based methods of text classification. Their results demonstrated that it was very clear that deep learning models, including CNNs and LSTMs, outperformed conventional machine learning models in distinguishing between authentic and fake content. The research highlighted the importance of sentiment and words as factors that help in detection of misinformation during times of global crisis.

Basarslan and Kayaalp (2020) applied machine learning algorithms on sentimental analysis on social media data. They found that algorithms like Naive Bayes, Support Vector Machines or Random Forests could successfully label sentiment polarities, but that their performance would differ based upon feature engineering methods. The paper highlighted the possibility of integrating lexicon-based and machine learning based techniques in order to enhance accuracy in sentiment classification.

Bhardwaj, Bharany, and Kim (2024) established a system of fake social media news and misleading campaigns detection with the help of sentiment analysis and machine learning. Their study has also shown that sentiment features when used with machine learning classifiers helped in identifying manipulative and biased material. The research supported the wider issue of sentimental detection in ensuring that digital platforms are not invaded with misinformation and malicious campaigns.

3. RESEARCH METHODOLOGY

The present research was an exploratory study of quantitative research design with 100 purposively selected social media posts processed, and transformed with TF-IDF and sentiment lexicon. Four machine learning algorithms (LR, SVM, RF, LSTM) were utilized to distinguish between sentiments, and three different analytical approaches (descriptive, predictive, correlational) were used to analyze sentiment distribution, model performance and feature importance.

3.1 Research Design

This research employs quantitative and exploratory approach to examine how social media interaction influences the human sentiments. The methodology is premised on machine-based sentiment analysis where social media posts are categorized as positive, negative and neutral. The design can support descriptive analysis of sentiment distribution and a predictive assessment of machine learning models.

3.2 Sample and Data Collection

The method used was purposive sampling where 100 social media posts were obtained on popular sites like Twitter and Facebook. In order to achieve this, Posts have been chosen to reflect both trending discussions, more general discussions and light exchanges. The small number of 100 samples makes the sample size manageable and achieves the goals of the study through demonstration of effectiveness of the machine learning methodologies applied to sentiment classification at hand and still fairly interpretable.

3.3 Data Preprocessing

The posts, which had been collected were preprocessed prior to analysis These involved the eliminations of URLs, emojis, stop words, and special characters. To standardize, normalization was carried out based on tokenization, stemming, and lemmatization to create standardization. And then all of the posts were labeled and categorized into the sentiment groups (positive, negative, or neutral) in order to train the supervised machine learning model.

3.4 Feature Extraction

Textual data were replaced with quantitative data by means of applying Term Frequency-Inverse Document Frequency (TF-IDF) and Sentiment Lexicon Scores. Other structural and contextual variables including the length of the post, the number of hashtags, retweet, favorite/share counts and user influence scores were also retrieved to complement the prediction accuracy.

3.5 Machine Learning Models

Four sentiment classifiers (based on machine learning) were used:

- **Logistic Regression (LR):** A baseline statistical model of polarity classification.
- **Support Vector Machine (SVM):** A good choice on high-dimensional text data.
- **Random Forest (RF):** Feature importance analysis is an ensemble learning technique.
- **Long Short-Term Memory (LSTM):** a deep learning model to learn each word interactions in a sequence.

3.6 Data Analysis

There were three stages through which the processed dataset was analyzed:

1. **Descriptive Analysis:** Analyzed sentiments distribution on 100 posts.
2. **Predictive Analysis:** Compared the four machine learning models in regards to their computation.
3. **Correlational analysis:** The degree of relationship between the measures of engagement (likes, comments, shares) and sentiment polarity was revealed. The importance of the attributes concerning the sentiment classification was determined by means of the Random Forest model.

4. DATA ANALYSIS AND INTERPRETATION

Table 1 and Figure 1 show how the sentiments are distributed in 100 posts on social media. The positive posts were evaluated as 35%, negative posts- 40, and neutral posts- 25. This distribution is reflected in the graphical representation in Figure 1 which indicates that there is a slight superiority of negative sentiments over positive and neutral sentiments.

Table 1: Distribution of Sentiments across Social Media Posts

Sentiment Type	Number of Posts	Percentage (%)
Positive	35	35
Negative	40	40
Neutral	25	25
Total	**100**	**100**

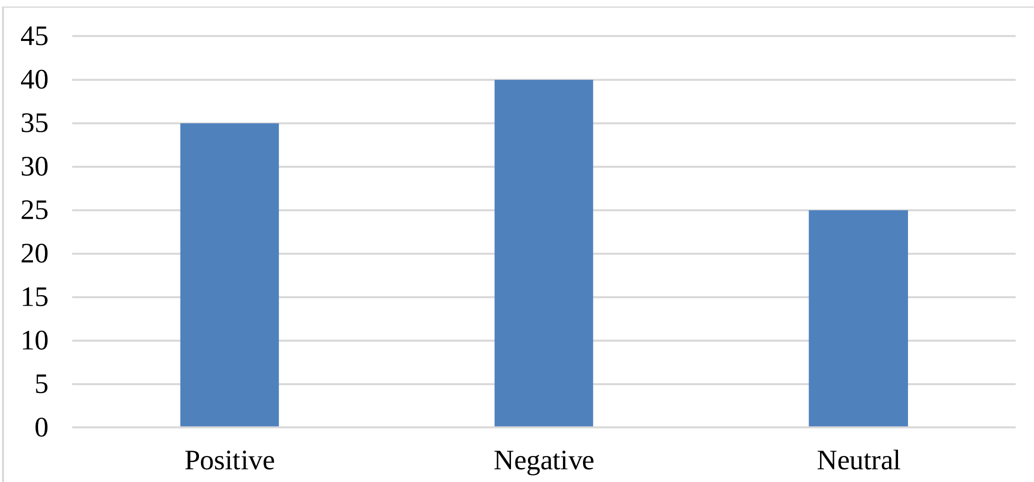

Figure 1: Graphical Representation of Distribution of Sentiments Across Social Media Posts

The results indicate that social media communication within the chosen sample is more orientated toward the negative emotional expression. This means that the online platforms tend to act as areas where individuals express their concerns, disagreement or frustrations freely as compared to positive sentiments. Nonetheless, the existence of a significant number of both positive and neutral posts indicates the diversity of the users interaction, meaning that even though negativity may prevail, social media itself is also a balanced arena when it comes to emotional interactions of various nature.

Table 2 and Figure 2 show the output of four machine learning experiments done to classify the sentiments on a sample of 100 posts. LR attained 75% accuracy followed by a slightly higher score by SVM and Random Forest of 78 and 80 respectively. The LSTM deep learning model showed a better classification performance compared to all the traditional models; it had the highest accuracy (84 percent), precision (83 percent), recall (82 percent) and F1-score (82.5 percent).

Table 2: Machine Learning Model Performance for Sentiment Classification

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Logistic Regression (LR)	75	74	73	73.5
Support Vector Machine (SVM)	78	77	76	76.5
Random Forest (RF)	80	79	78	78.5
LSTM (Deep Learning)	84	83	82	82.5

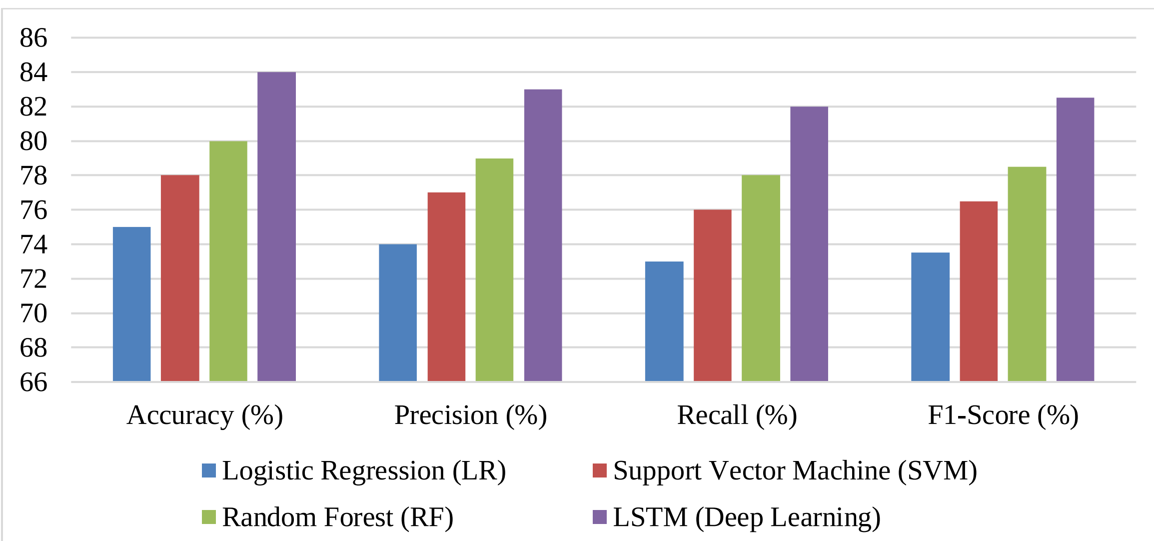

Figure 2: Graphical Representation of Machine Learning Model Performance for Sentiment Classification

The findings indicate that the evolutionary deep learning models such as LSTM are found to be more efficient in terms of capturing the contextual and sequential nature of textual data than workhorse machine learning algorithms. Although SVM and Random Forest are known to be reliable models, their deficiency in dealing with the complex language structures is exposed to

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comparison with LSTM. This implies that deep learning approaches are more effective and accurate in sentiment analysis of data in social media.

In Table 3 and Figure 3, a correlation between the metrics of engagement (likes, comments, and shares) and sentiment polarity was presented. The findings suggest that positive and negative sentiments are both slightly related to greater engagement with negative ones related by a slightly greater margin (likes r = 0.65, comments r = 0.55, shares r = 0.50). Neutral sentiments, as compared to any of the engagement measures, are relatively low with values that range between 0.20 and 0.30.

Table 3: Correlation between Engagement Metrics and Sentiment Polarity

Engagement Metric	Positive Correlation (r)	Negative Correlation (r)	Neutral Correlation (r)
Likes	0.60	0.65	0.30
Comments	0.50	0.55	0.25
Shares	0.45	0.50	0.20

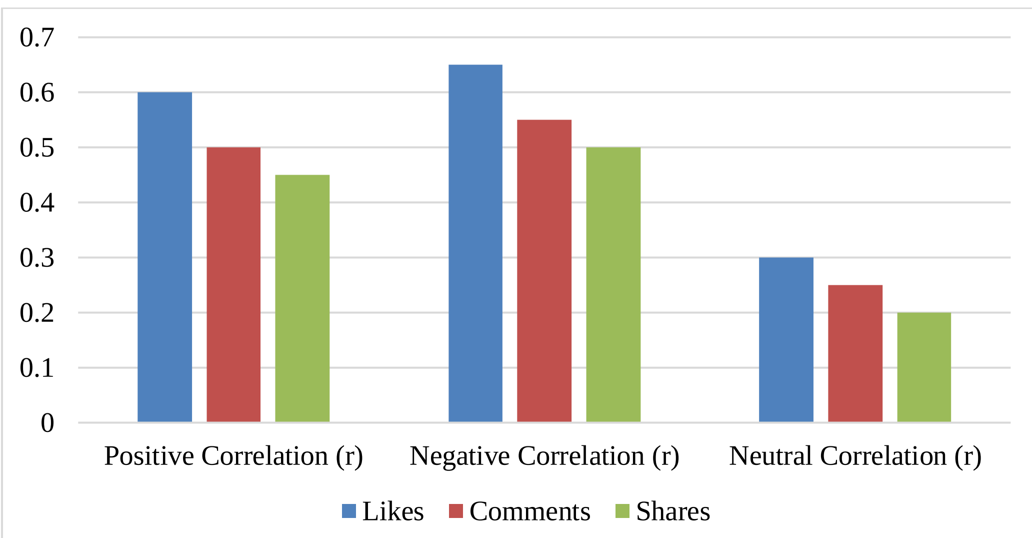

Figure 3: Graphical Representation of Correlation between Engagement Metrics and Sentiment Polarity

Such results can be interpreted to mean that content that is of an emotional nature (good or bad) is likely to draw more user activity in a social media platform. Negative sentiments, however, can be

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used to elicit even stronger responses, which are likely to be caused by the fact that users tend to respond more rapidly to controversial, critical or alarming contents. The less emotionally charged posts (neutral) have the lowest engagement, which points out to the significance of the intensity of sentiment in the determination of interactions online.

Table 4 and Figure 4 show that the most important features were related to that particular side of the debate. TF-IDF was rated as the most influential factor, contributing to model performance by 30 percent and Sentiment Lexicon Score followed rating at 22 percent. The percentages of Post Length, and of Number of Hashtags were 16 and 12, respectively. The least influential and hence the final two were Length of Campaign Optimization and User influence Score where the contribution in both were 10 percent.

Table 4: Feature Importance in Sentiment Prediction

Feature	Importance Score (%)
Word Frequency (TF-IDF)	30.0
Sentiment Lexicon Score	22.0
Post Length	16.0
Number of Hashtags	12.0
Engagement Metrics	10.0
User Influence Score	10.0

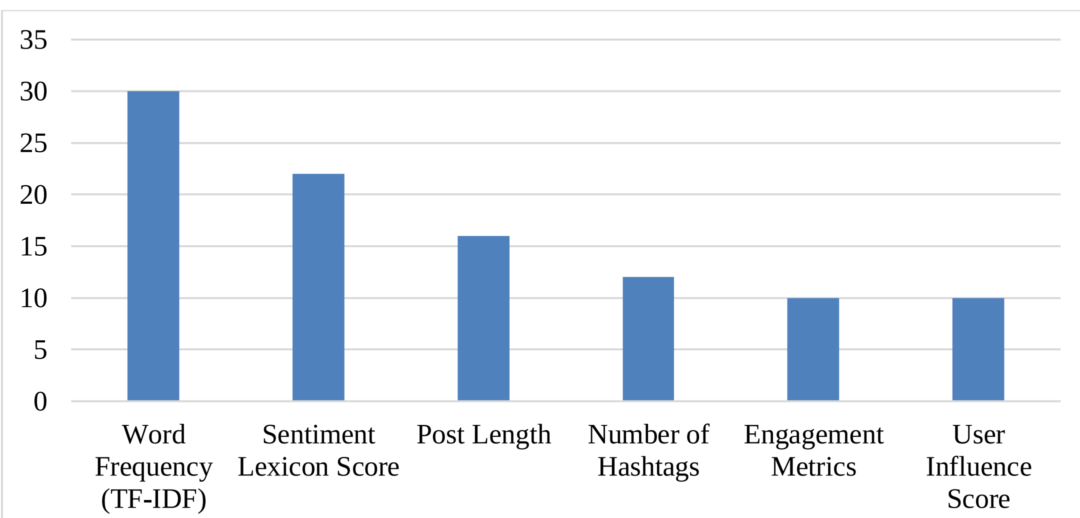

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Figure 4: Graphical Representation of Feature Importance in Sentiment Prediction

The outcomes indicate that word use patterns and sentiment levels based on lexicon factor are of a very crucial importance in influencing sentiment. Structural elements such as post length and hashtags add meaning as well albeit not to the same degree. Engagement features and user influence have rather little predictive power implying that the text content of posts stands out as determinative in sentiment analysis rather than the other factors, such as popularity executed by the user and level of user interaction.

5. CONCLUSION

This paper discussed the effects of social interactions on the emotions of humans via machine learning model where the research was performed using 100 social media posts as the sample. The analysis demonstrated that the negative sentiments overtook the positive and neutral expressions by a margin, emphasizing the tendency of the users to express their concern and disappointments much more freely online. Experiments in the area of machine learning confirmed that activities like Logistic Regression, SVM, and Random Forest had decent levels of accuracy, but the LSTM deep learning model provided more accurate results by extracting sequential and contextual patterns in the text. Correlational analysis also revealed that positive as well as negative sentiment had a very strong linkage with increased engagement but the negative posts received a little more engagement compared to the positive posts and the neutral posts also received negligible attention. TF-IDF word frequencies and sentiment lexicon were the most important predictors of sentiment, while user sentiment and influence and engagement metrics appeared to generate a secondary effect. In general, it has been proven that social media sites do not only reflect but also magnify human emotions and that machine learning is a highly useful method of discovering such trends giving beneficial information to researchers, marketing companies as well as government planners who want to understand driver behavior on the internet.

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