A new mining and decoding framework to predict expression of opinion on social media emoji's using machine learning models

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ABSTRACT

This research work proposes a new framework mining and decoding (MindE) to predict the expression of opinion on social media emojis using machine learning (ML) models. Expression of opinion can be predicted with short messages on social media. This study used two groups of ML algorithms, convolutional neural network (CNN) ImageNet and CNN AlexNet classifier, and finally, applied the decision tree classifier to predict the type of expression. A recent dataset was taken from Kaggle, an open-source dataset consisting of 7476 rows of emojis for expression of opinion prediction. Accuracy was computed with a G power of 80%, and the experiment was repeated 20 times using both models. After the introduction of the proposed MindE framework, the performance of an expression of opinion prediction will be analyzed with accuracy level. The CNN ImageNet achieved an impressive 97.32% accuracy, whereas the CNN AlexNet algorithm reached only 85.98%. The independent sample T Test indicated a p-value of 0.001, which is below the significance level of 0.05. This suggests that the performance difference between the two ML algorithms is statistically significant. Consequently, the results strongly support the proposed framework "MindE" to predict the expression of opinion on social media emojis.

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1. INTRODUCTION

The usage of emojis is common from past one decade in social media like Twitter, WhatsApp, and Instagram. At the same time the meaning of each emoji has universal understanding between individuals [1]. A promising avenue for innovation in emoji prediction lies in the development of machine learning (ML) algorithms with various social media platforms has huge impact in understanding the expression of opinion of each individual [2]. Emojis have transformed from basic emotions into a multifaceted and significant mode of communication, impacting diverse areas of our personal and professional lives, shaping how it will engage, convey emotions, and communicate information in the contemporary digital landscape [3]. Consequently, emoji research has gained prominence in academia, with scholars from diverse domains such as computing, communication, marketing, and behavioural science delving into this subject.

This study investigated the effects of emoji usage on social media with ML technologies. While earlier studies have explored the impact of traditional usage of emojis, they have not explicitly addressed its influence on ML algorithms' suggestions. Therefore this research study suggests a new framework mining and decoding (MindE) to understand the expression of opinion of each individual using emojis. Innovation involves the practical implementation of novel ideas leading to improvements compared to prior methods [3]. One potential innovation worth exploring is the integration of predictive text technology with emoji prediction. This research study investigated many existing reviews of the evolutionary history and usage patterns of emojis. It also delves into the emotional and linguistic characteristics of emojis, provides a summary of emoji-related research findings in various disciplines, and suggests future research directions [4]. By using innovation, emojis are predicted from text by applying advanced ML algorithms that will enable two people to communicate their feelings to one another effectively and quickly [5]. By using innovation, emojis are predicted from text by applying advanced ML algorithms that will enable two people to communicate their opinions to one another. Emojis can be added to upload photographs on Twitter, WhatsApp, and Instagram, as stickers or you can use large, recognizable emojis in the messenger app or any social media application. Innovation will continue to play a major role in driving the field of emoji prediction forward [6]. We found that traditional emoji usage in social media takes a long time to apply for correct expression by the users, therefore this research study correlates with proposing a new framework. The proposed method in this study tended to have an inordinately higher proportion of ML based technology to effectively predict suitable expression using the proposed MindE.

2. LITERATURE SURVEY

Google Scholar and Science Direct have published over 680 and 782 respectively, on emoji prediction using a range of datasets, ML methods, and methodologies [7]. After reviewing several articles, we have concluded that the most appropriate and relevant article for this research is Lee *et al.* [7], to enhance the emoji based communication with predictive systems that utilize advanced ML classifiers to suggest appropriate emojis, involves collecting a dataset of text messages paired with emojis, extracting relevant features from the text, selecting suitable classifiers, training and evaluating their performance, and iteratively refining the models to improve emoji prediction accuracy and user experience [7]. Also another study says that emoji prediction with image to text conversion and text to image conversion through ML with natural language processing with part of speech processing [8]. Also few study says that the assessing emoji with modern text processing tools are helpful for social media users for instant pick and drop [9]. By reviewing all these information, this paper suggesting a new framework “MindE”. This framework using the optimal ML algorithm suggested by this part of the study [10]. This research work start with a sample emoji’s used for social media users and presented in Figure 1, this is because the article employs suitable and relevant algorithms to predict emojis from text. The figure has emoji with text connected with information for understanding the ease of use.

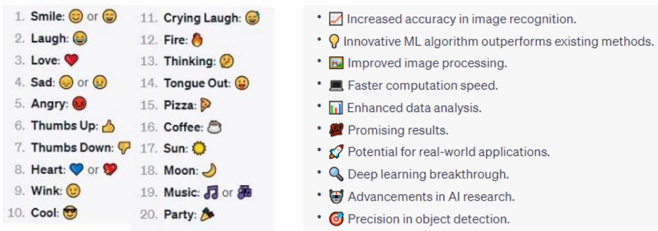

Figure 1. Few samples of emoji and meaning to express the opinion of the individual

The accuracy prediction of emoji from expression of opinion text or emoji using various existing ML algorithms such as support vector machine (SVM), naive bayes (NB) algorithm models are having 72 and 68 percentage [11]. These two SVM and NB prediction with modified classifer gives best performance for basic expression of opinion from text to emoji, at the same time for complex systems known as long statement of expression to predict equivalent emoji has lesser accuracy [12]. Therefore this research study suggesting a new framework. Few studies already evaulaved the expression of opinion from text to emoji for sentimental analysis to observe the social network impact on society happenings, these studies has few impact on election voteing change among the groups of individuals from various situations and environments [13].

The convolutional neural network (CNN) AlexNet ML algorithm also used in few studies to predict the emoji equivalent to expression of opinion with 85.98% of accuracy. It has been observed to be lower than CNN in some cases when predicting text to emoji using ML algorithms [14]. This raises a research gap that needs to be addressed to understand why AlexNet performs less accurately and how to improve it. To address this gap, some potential areas of investigation could include exploring the impact of training dataset size and composition on the performance of various ML algorithms. Investigating the effect of hyperparameter tuning, such as maximum depth, minimum number of samples, and number of features considered when splitting a node, can also be beneficial in improving AlexNet performance.

Additionally, examining the impact of pre-processing techniques like tokenization, stemming, and stop-word removal on both algorithms can help improve their accuracy [14]. Evaluating different ML models such as random forest or decision trees can provide insights into which architecture performs best for text to emoji prediction tasks [15]. Finally, investigating the impact of different CNN architectures, including varying numbers of convolutional layers and filters, different pooling strategies, and the use of dropout or batch normalization, can improve CNN's performance [16]. This research aims to employ ML algorithms to analyse text and convert it into emojis. The study compares two algorithms, namely linear support vector machine (LSVM) and long short-term memory (LSTM), to determine which one provides better accuracy in converting text to emojis and giving as a input to the proposing a new framework to predict expression of opinion [17].

3. RESEARCH METHOD

The proposed framework “MindE” used one optimal ML algorithm for this two ML algorithms such as CNN AlexNet and ImageNet classifier are taken to predict better accuracy and less loss parameters. To predict the sample size, this experiment was conducted using a fixed alpha (α) value of 0.05 and a calculated G-power value of 80% on G-power tool. The algorithms were executed 20 times (N=20) during the experiment [18]. The test setup of the project was done on Lenovo ThinkPad with 8 GB RAM, Intel i5 8th generation processor, 1 TB storage and Windows operating system. The data used in this research is emoji prediction using text, an open-source data from Kaggle [19]. This file contains text with different content. The file size is 4 MB and contains a total of 7,476 columns [20]. The data is divided into training and testing. The training file contains 6,018 lines and the test file contains 1,458 rows of dataset. To achieve higher accuracy in predicting the dataset, this research employs two different methods: the CNN AlexNet and CNN ImageNet classifier, which is run 20 times with varying data sizes to ensure accuracy.

The CNN AlexNet architecture shown in Figure 2. In this prepared dataset first applying for various data cleaning procedures then examined with CNN AlexNet classifier with parameter adjustment, later applied the training set to predict the emoji. After predicting the emoji, it will used on the proposed “MindE” framework.

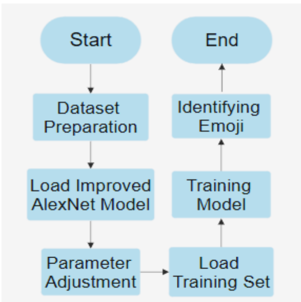

Figure 2. CNN AlexNet architecture to predict emoji

The CNN ImageNet architecture shown in Figure 3. In this dataset collected from various social media such as Twitter, WhatsApp and Instagram are applied for preprocessing procedures then applied CNN ImageNet classifier, later applied the training model to predict the emoji. After predicting the emoji, it will apply on the proposed “MindE” framework. The two CNN AlexNet and CNN ImageNet ML algorithms are applied to a total of 40 samples and the results are recorded individually. The same process is repeated 20 times with different data sizes to ensure accuracy. Data are analyzed using statistical package for social sciences (SPSS) version 29. The results of the two methods are then compared to determine which one has the highest accuracy. The best algorithm with the highest accuracy is selected for predicting the emoji to find the expression of opinion using proposed “MindE” framework.

The two CNN AlexNet and CNN ImageNet ML algorithms are applied to a total of 40 samples and the results are recorded individually. The same process is repeated 20 times with different data sizes to ensure accuracy. Data are analyzed using SPSS version 29. The results of the two methods re then compared to determine which one has the highest accuracy. The best algorithm with the highest accuracy is selected for predicting the Emoji to find the expression of opinion using proposed “MindE” framework.

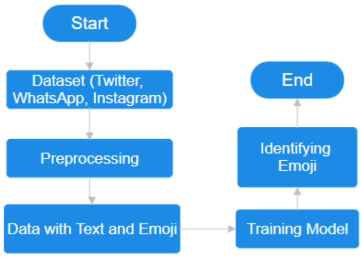

Figure 3. CNN ImageNet architecture to predict emoji

4. RESULTS AND DISCUSSION

The results are showing the performance of CNN AlexNet and CNN ImageNet algorithms using a dataset consisting of 7,476 samples. For training, approximately 80.5% of the data (around 6,018 samples) is used, leaving about 19.5% (approximately 1,458 samples) for testing. In Table 1, you can observe the results obtained by running the CNN AlexNet and CNN ImageNet ML algorithms on the dataset, where the dataset size varies. This was done while allocating 80.5% of the data for training and reserving 19.5% for testing, and this process was repeated in 20 different iterations with the total of 100% with 7,476 rows of data. Table 2 the 20 iterations to derive essential statistical metrics for both the CNN AlexNet and CNN ImageNet algorithms. These metrics encompass the mean error value, standard deviation, and standard error of the mean. Interestingly, it was observed that the mean error for the CNN AlexNet algorithm (75.8680%) outperformed that of the CNN ImageNet algorithm (88.0435%).

Table 1. The accuracy results for the initial dataset when N=1 is 97.32% for CNN ImageNet algorithm and 85.98% for CNN AlexNet algorithm

Sample (N)	Dataset size/rows	CNN ImageNet accuracy in %	CNN AlexNet accuracy in %
1	7476	97.32	85.98
2	7397	96.98	84.56
3	6932	95.44	83.23
4	6765	94.35	82.42
5	5234	93.32	81.23
6	5100	92.33	80.99
7	4900	91.45	79.56
8	4564	90.24	78.66
9	4324	89.77	77.56
10	4289	88.33	76.65
11	4123	87.65	75.44
12	4200	86.98	74.23
13	3768	85.34	73.45
14	3324	84.98	72.76
15	3800	83.21	71.98
16	2456	82.43	69.89
17	2387	81.98	68.88
18	2222	80.66	67.56
19	1098	79.68	66.88
20	1234	78.43	65.45

Table 2 presents the outcomes of the statistical analysis conducted on these 20 samples. For the CNN ImageNet algorithm, the outcomes include a standard deviation of 5.86069 and a standard error of 1.31049. In contrast, the CNN AlexNet algorithm exhibits a standard deviation of 6.20364 and a standard error of 1.38718. The two-tailed significance value 'p', with a 95% confidence interval, was found to be less than 0.001, thereby supporting our hypothesis. Moreover, Table 3 provides insights into the corresponding changes in input values (independent variables) and output values (dependent variables).

Table 3 the independent sample T-test of the significance level CNN ImageNet and CNN AlexNet algorithms results with a significant value of two tailed tests ($p=0.000$, $p<0.05$) with a 95% confidence interval. Therefore, both the CNN ImageNet and the CNN AlexNet algorithms have a significance level less than 0.05 with a 95 % confidence interval. The p significant difference between two algorithms is less than 0.001. Input dataset from Twitter, WhatsApp, and Instagram are taken to apply preprocessing by doing spelling correction, Tokenization, stop-word removal, removal of number, stemming, and lemmatization. After that the processing text and emoji data are sent to extract features. Later the CNN AlexNet and ImageNet algorithms are applied to predict accurate emoji with higher accuracy and less loss using performance metrics. Finally, expression of opinion will be predicted from the emoji's and this is shown in Figure 4. The mean accuracy of the CNN ImageNet algorithm was remarkably high at 88.04%, in contrast to the CNN AlexNet method, which achieved an accuracy of 75.87%, as indicated in the Figure 5 and accuracy from 20 samples of the CNN ImageNet algorithm having 97.32% and CNN AlexNet with 85.98% as shown in Figure 6. Based on these results, it is evident that the CNN ImageNet algorithm significantly higher than CNN AlexNet in terms of accuracy.

Table 2. The outcomes of the statistical analysis conducted on these 20 samples

Group statistics					
Accuracy	Algorithms	N	Mean	Standard Deviation	Standard Error Mean
	CNN ImageNet	20	88.0435	5.86069	1.31049
	CNN AlexNet	20	75.8680	6.20364	1.38718

Table 3. Independent sample T-test of the significance level CNN ImageNet and CNN AlexNet algorithms

Precision	"Levene's test for equality of variances"		Statistical test					"95% of the confidence interval of the difference"	
	F	Sig.	t	df	Signific (2-tailed)	Mean difference	Std Error difference		
Equal Variance Assumed	0.100	0.754	6.380	38	0.000	12.17550	1.90831	8.31233	16.03867
Equal Variance Not Assumed			6.380	37.878	0.000	12.17550	1.90831	8.31192	16.03908

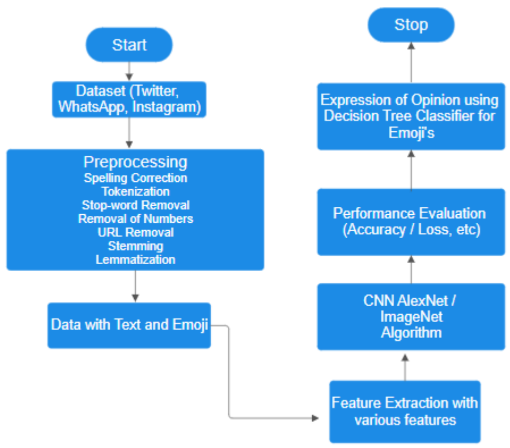

Figure 4. Proposed framework "MindE" to predict expression of opinion from a set of emoji's on various social media network system

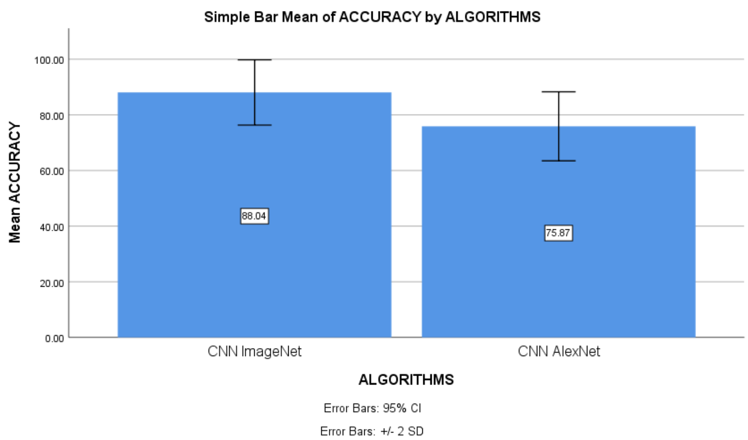

Figure 5. Comparison of CNN ImageNet algorithm and AlexNet algorithm in terms of mean performance

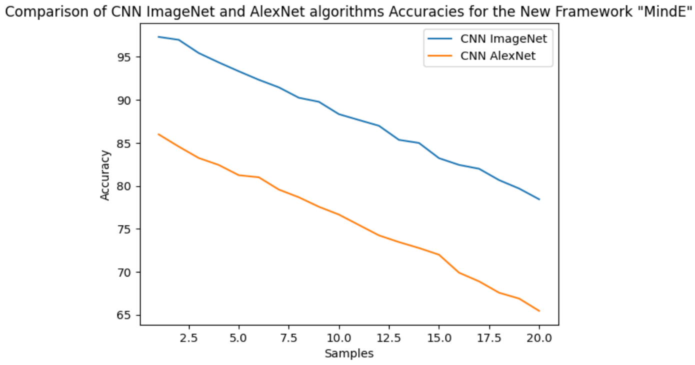

Figure 6. Results of emoji prediction performance values of CNN ImageNet (blue in colour with 97.32%) and CNN AlexNet (orange in colour with 85.98%) across the samples

The mean error of ImageNet is better than the AlexNet algorithm and the standard deviation of the ImageNet is slightly better than the AlexNet algorithm. X-Axis: CNN ImageNet vs CNN AlexNet algorithm Y-Axis: Mean accuracy detection + 2 SD. To formally compare the accuracy of the two algorithms, an independent t-test was performed, which revealed a statistically significant difference with a low p-value of 0.001. The conclusive analysis presented in Figure 4 affirms that the newly introduced framework “MindE” has selected the CNN ImageNet algorithm and applied on decision tree algorithm to predict expression of opinion based on the emoji.

Figure 6 provides a visual comparison of the accuracies achieved by the CNN ImageNet and CNN AlexNet algorithm across the sample dataset. The Blue line represents the accuracy range of the CNN ImageNet algorithm, while the orange line illustrates the accuracy range of the CNN AlexNet algorithm. The SPSS software is utilized to perform statistical analysis and compute various key metrics such as mean, standard error and standard deviation of the mean for both ML algorithms [21]. These algorithms are utilized for predicting emojis based on various input preprocessed dataset. The dependent variable under examination in this analysis is the predicted emoji, while the independent variables are characteristics of the input data, including the size, color, and shape of the image, as well as the input text itself [22]. Overall, SPSS is a useful tool for conducting statistical analyses of data related to emoji prediction using these ML algorithms.

The research conducted in this study indicates that predicting emojis from text is more effective when the text includes significant keywords such as "smile," "angry," "cry," and "heart" as opposed to longer sentences [23]. The study also concludes that the CNN ImageNet algorithm performs exceptionally well in predicting emojis from text. Contrary to the findings of the aforementioned study, recent research suggests that using a CNN of hidden layer 2 with 128 epochs can achieve an accuracy of 97.32%, outperforming alternative ML models such AlexNet, random forests, logistic regression, LSVM, and LSTM. This research emphasizes the significance of hidden layers in CNNs when dealing with discrete data [24], [25]. A solitary line is not sufficient to attain the optimal boundary decision, underscoring the necessity of incorporating hidden layers for achieving this goal. The present study focuses solely on the prediction technique using datasets related to emoji prediction as input. The proposed framework “MindE” focus on predicting the expression of opinion based on emoji generated by CNN ImageNet ML algorithm.

This study explored a comprehensive usage of emojis on social media concerning scenarios. However, further and in-depth studies may be needed to confirm its right usage in the right place when the expression of text is very complex, especially regarding abbreviated words and sentences with regional practice. Our study demonstrates that emojis are useful only when text information with simple sentences is converted whenever required with automated ML-based proposed MindE framework and it is more resilient than traditional use of emojis. Future studies may explore the cloud-based automated tools for converting text into emojis with feasible ways of producing emojis in simple interpretations.

5. CONCLUSION

Recent observations suggest that the usage of emojis is a regular practice in most social media. Our findings provide conclusive evidence that this phenomenon is associated with ML technologies with the MindE framework will change, not due to elevated numbers of text-to-emoji conversions. Therefore, the proposed a new framework “MindE’ to predict the expression of opinion on social media emojis using ML models also expression of opinion can be predicted with short messages on social media like Twitter, WhatsApp, and Instagram. For this ML algorithms such as CNN ImageNet and AlexNet are used, then classified the type of emoji using the decision tree algorithm. This study used two groups of ML algorithms, a CNN ImageNet and a CNN AlexNet classifier, and finally, applied the decision tree classifier to predict the type of expression. The main limitation of this research study is only used two ML algorithms such as CNN ImageNet and CNN AlexNet and also analyzed the statistical forecasting using an independent sample T Test with two groups. In the future, more than two ML algorithms (with many groups) will use the analysis of variance (ANOVA) statistical method to predict the emoji from text.

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