**INTER DEPARTMENTAL PROJECT REPORT**

on

**“Emoji Sentiment Analysis Using Feedforward Neural Networks”**

**Submitted**

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**CERTIFICATE**

This is to certify that the Field Project entitled **“Emoji Sentiment Analysis Using Feedforward Neural Networks”** that is being submitted by 221FA04159(V. Leeladhar),221FA04267(O. Vasavi Mounika),221FA04339(G. Radhika), 221FA04424(B. Harshith) for partial fulfilment of Field Project is a bonafide work carried out under the supervision of Dr.S.DEVA KUMAR, M.Tech., Professor, Department of CSE.

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**DECLARATION**

We hereby declare that the Field Project entitled “**Sentiment analysis of Amazon reviews using machine learning techniques**” is being submitted by 221FA04159(V. Leeladhar),221FA04267(O. Vasavi Mounika),221FA04339(G. Radhika), 221FA04424(B. Harshith) in partial fulfilment of Inter Departmental Project course work. This is our original work, and this project has not formed the basis for the award of any degree. We have worked under the supervision of Dr. S. DEVA KUMAR, M.Tech., Professor, Department of CSE.

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## **ABSTRACT**

In the evolving landscape of digital communication, emojis play a critical role in enriching text-based conversations, offering insights into user sentiment, context, and demographics. This study aims to explore the patterns of emoji usage across platforms, focusing on user age, gender, and sentiment analysis. Utilizing a dataset comprising emoji usage, platform, and demographic information, we applied several data visualization techniques to understand the distribution of emoji usage across user categories. To deepen our analysis, we employed label encoding for categorical variables, followed by sentiment analysis using the TextBlob library. A multi-class classification neural network was then developed to predict the context of emoji usage, incorporating early stopping for improved model performance. Our results demonstrate clear demographic trends in emoji usage and reveal sentiment variations based on the context and platform. Additionally, outlier detection techniques identified inconsistencies between emoji sentiment and expected emotional responses. The model achieved a satisfactory accuracy level in predicting user context, as evidenced by performance metrics. This work contributes to the understanding of the intersection between digital communication, sentiment, and user demographics, with applications in social media analytics and marketing.

Keywords— Emoji analysis, sentiment analysis, neural networks, demographic analysis, TextBlob, Multi-Class Classification.

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# **CHAPTER 1**

# **INTRODUCTION**

1. **INTRODUCTION**

**1.1 Overview of Emoji Usage in Digital Communication**  
Emojis have revolutionized digital communication by adding emotional context and enhancing textual interaction. Originally introduced as simple smiley faces or objects, emojis have expanded into a comprehensive symbolic language that is used across various platforms such as social media, messaging apps, and emails. Emojis convey emotions, tone, and even cultural nuances that plain text might fail to capture. Their usage is particularly important in environments where non-verbal cues are missing, such as in instant messaging or social media posts.

**1.2 Importance of Sentiment Analysis in Virtual Interaction**  
As the volume of online communication grows, understanding user sentiment through emojis has become increasingly critical. Sentiment analysis, traditionally applied to text, is now extending its scope to emojis. By analyzing emoji usage, businesses and researchers can gather insights into customer satisfaction, emotional engagement, and even political opinions. Accurately identifying the sentiment behind emoji usage is key to improving user experience, targeted marketing, and feedback analysis in digital platforms.

**1.3 Applications of Machine Learning in Emoji-based Sentiment Detection**  
Machine learning has provided a robust framework for performing sentiment analysis at scale. Various algorithms, including artificial neural networks (ANN), are now employed to analyze the combination of text and emoji usage. These models are capable of learning intricate patterns in data, identifying the sentiment expressed through emojis, and offering predictions about user emotion. Applications range from social media monitoring to customer service analysis, where businesses can track user sentiment in real-time.

# **CHAPTER 2**

# **LITERATURE SURVEY**

**2.LITERATURE SURVEY**

A literature survey is a critical review of the studies and academic contributions already existing within the body of knowledge relevant to the issue under investigation. While synthesizing key findings, methodologies, and theories into other research works, it shows states of progress on the one hand and gaps on the other hand. In the process, it puts the current study not only into a warranted context but also into a justified need. This literature review will help researchers place their own work within the broader knowledge already in existence-that is, present exactly how the study builds on, contrasts with, or fills a gap left by previous research.

**2.1 Existing Research in Sentiment Analysis**

This paper explores sentiment analysis by classifying text into positive, negative, or neutral sentiments using machine learning techniques. It provides a foundational understanding of the underlying emotions in textual data and discusses the challenges in accurate classification due to varying context and expression of emotions in text.[1] The authors discuss the integration of emojis in faculty feedback using ChatGPT, highlighting how emojis can enhance the richness of feedback. The paper emphasizes the role of AI in embedding emojis and how it improves communication effectiveness in educational settings.[2] This paper focuses on tweet sentiment classification using emojis and emoticons. The study shows how emojis and emoticons improve sentiment detection accuracy, particularly in social media content, where they carry significant emotional weight.[3]. This research examines emoji classification using the Random Forest Classifier, providing insights into the effectiveness of this machine learning model in distinguishing various emoji-based sentiments, which aids in more nuanced sentiment analysis.[4] .The paper presents a method for predicting sentiment based on emoji usage by leveraging sentiment analysis. The authors show how emoji sentiment prediction can complement text-based analysis for more accurate sentiment insights.[5] . This paper introduces the Emo-SL Framework, which uses text-based features and machine learning for emoji sentiment analysis. It demonstrates the development of an emoji sentiment lexicon, which helps improve sentiment classification accuracy in various contexts.[6]. The paper surveys deep learning models for sentiment analysis that integrate both textual and emoji-based features. It explores different architectures and techniques for enhancing sentiment detection in social media and informal communication.[7]. This study examines how gender influences emoji sentiment analysis among Arabic users in digital networks. The paper provides insights into how cultural and gender differences affect the interpretation of emojis in sentiment analysis.[8] . The paper provides a fine-grained analysis of emoji sentiment based on Twitter user attributes. It highlights the relationship between user demographics and emoji usage, offering a more personalized approach to sentiment analysis.[9] . This study applies multi-class sentiment analysis over social networks using text and emoji-based features. The paper highlights how combining these features enhances sentiment prediction accuracy across diverse social media platforms.[10]. The authors focus on machine learning applications for sentiment analysis in social media, combining text with emojis for enhanced sentiment detection. The paper demonstrates the growing importance of emojis in improving machine learning models' performance.[11].This paper investigates sentiment analysis using learning approaches specifically for Turkish tweets. It highlights the importance of considering language-specific nuances in emoji usage when performing sentiment analysis.[5]. This study introduces sentiment analysis and emoji mapping, showing how mapping emojis to sentiment categories can enhance the detection of user emotions in social media content, improving sentiment prediction.[12].The paper investigates Twitter sentiments by analyzing emotions and opinions through sentiment analysis. It emphasizes the role of emojis in enhancing the accuracy of sentiment classification in large-scale social media datasets.[1]. This study discusses the role of emojis in sentiment analysis of financial microblogs. It highlights the impact of emojis in conveying sentiment in financial communications, which can affect market analysis and decision-making.[13]. The paper explores how emoji sequences improve sentiment cognition by analyzing how different emoji combinations influence sentiment perception. It shows how sequence-based emoji analysis can offer deeper insights than single emoji analysis.[14]. The authors utilize nature-inspired algorithms for sentiment analysis of reviews. The paper discusses how combining emoji sentiment with nature-inspired algorithms can optimize sentiment prediction models for real-world applications.[15].This study examines sentiment analysis of Google Play and App Store reviews, highlighting the integration of emojis for better sentiment insights. It shows the importance of emoji usage in user feedback and review classification.[16]. The paper mines comments and sentiments from YouTube Live chat data, analyzing how emojis in live chat affect sentiment trends. It shows how real-time emoji analysis helps capture the dynamic nature of user sentiments during live events.[17]. This study applies a multinomial Naive Bayes classifier for Twitter sentiment analysis, incorporating emoji features. It demonstrates how emoji-based features can enhance the performance of traditional text-based sentiment models.[18].Explored the use of deep neural networks for multi-class sentiment classification, demonstrating the effectiveness of DNNs in capturing complex sentiment patterns in large datasets. Their work laid the groundwork for applying neural networks to sentiment analysis, offering a strong foundation for classifying nuanced emotional content in text.[19] proposed a deep neural network model to anticipate and predict emoji usage, revealing the power of DNNs in enhancing user interaction analysis by predicting emoji selection based on textual context. This research advanced emoji prediction as a key component of sentiment detection in digital communication.[20]. Focused on hand-drawn emoji recognition using convolutional neural networks (CNNs), introducing an innovative approach for recognizing and interpreting user-drawn emojis. Their model provided high accuracy and demonstrated the potential of CNNs in real-time, user-generated content classification.[21]

**2.2 Challenges in Classifying Emoji Usage and Sentiment**  
The classification of emoji sentiment presents several challenges. Unlike text, where words have relatively fixed meanings, emojis can be interpreted differently depending on the platform (iOS vs. Android), culture, or even individual user preferences. Additionally, a single emoji may carry multiple sentiments depending on the surrounding context. The variability in emoji interpretation adds complexity to the task of sentiment classification. Another challenge arises from the non-standard usage of emojis, where users might use emojis in ways that deviate from their intended meanings.

**2.3 Motivation for Using Neural Networks in Sentiment Analysis**  
Given the complexity of emoji usage and interpretation, traditional machine learning algorithms such as logistic regression and decision trees often fall short in accuracy. Neural networks, particularly deep learning models like artificial neural networks (ANN), offer the ability to model non-linear relationships in data, making them better suited for understanding the contextual usage of emojis. Their capacity for learning from large amounts of data and extracting meaningful features from raw inputs has motivated their use in emoji-based sentiment analysis.

# **CHAPTER 3**

# **METHODOLOGY**

**3. METHODOLOGY**

**3.1 Input Dataset and Features**

**3.1.1 Dataset Description**  
The dataset used in this study includes records of emoji usage from various social media platforms, including metadata such as user demographic information (age, gender) and corresponding sentiment labels (positive, negative, or neutral). Each record represents a user interaction containing text and emojis, along with the platform used for the interaction.

**3.1.2 Target Variables: Emoji Categories, User Demographics, and Sentiment**  
The primary target variables for this analysis are emoji categories (grouped by Emoji, Platform, Context, etc.), user demographics (age, gender), and the sentiment conveyed (positive, negative, or neutral). This will enable a multi-dimensional analysis of emoji usage patterns and their emotional contexts.

**3.2 Data Pre-processing**

**3.2.1 Handling Missing Data and Outliers**  
To ensure the integrity of the analysis, missing data for demographic fields and platform types were handled by either imputing median values or excluding the records, depending on the percentage of missing data. Outliers in emoji usage, such as users who use an excessive number of emojis compared to the norm, were identified and handled using outlier detection methods.

**3.2.2 Text and Emoji Preprocessing**

**3.2.2.1 Tokenization and Lowercasing**  
Tokenization was applied to split text into individual words, and all words were converted to lowercase to ensure uniformity. Emojis were treated as separate tokens and were standardized for consistency across platforms.

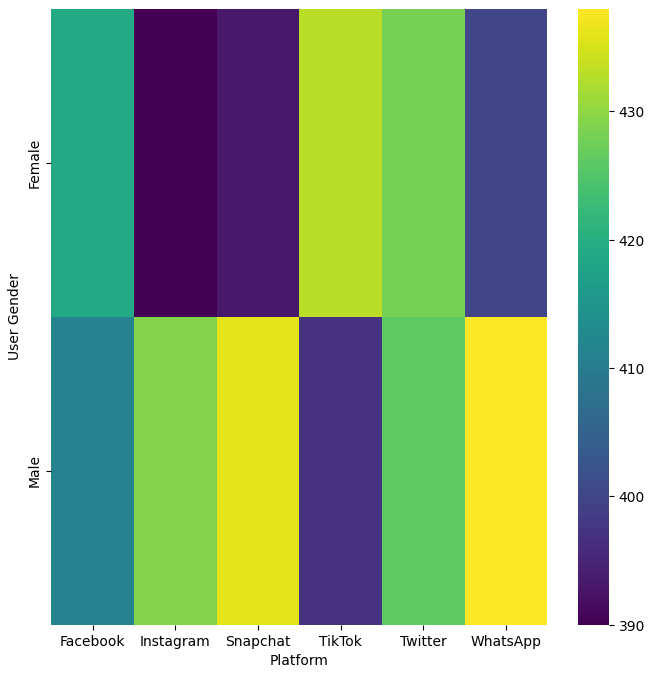
**3.2.2.2 Stop word Removal, Punctuation, and Emoji Cleaning**  
Non-informative words (stop words) were removed, along with irrelevant punctuation. Emojis were cleaned and categorized into pre-defined groups (e.g., smileys, gestures, animals) for easier analysis.

**3.3 Feature Extraction**

**3.3.1 Label Encoding for Categorical Variables**  
Categorical variables, including user demographics and emoji categories, were label encoded to convert them into numerical format for model input. This allowed the ANN to process and learn from the demographic and emoji usage patterns.

**3.3.2 Sentiment Assignment with TextBlob**  
Sentiment scores were assigned to each text snippet using the TextBlob library, which generates a polarity score indicating positive, negative, or neutral sentiment. These scores were combined with emoji usage data to improve the overall sentiment classification.

**3.3.3 Emoji Usage and Demographic Pattern Visualization**  
Several visualizations, such as plots and heatmaps, were created to explore the relationship between demographic factors and emoji usage patterns. These helped highlight key differences in how different age groups or genders use emojis.



**Figure 3.1**

**Platform vs User Age
**

**Figure 3.2**

**Context by user Age
**

**Figure 3.3**

**3.4 Model Building**

**3.4.1 Artificial Neural Network (ANN) for Sentiment Analysis**  
The core model for this project is an artificial neural network (ANN) that was trained to classify sentiment based on emoji usage and text data. The input features included the tokenized text, emoji categories, and demographic data, while the output was the predicted sentiment class.

**3.4.2 Multi-class Classification of Emoji Context**  
The ANN was trained to perform multi-class classification, predicting not only the sentiment but also the context in which an emoji was used (e.g., happy, sad, confused). This added another layer of complexity to the analysis but offered deeper insights into emoji usage.

**3.5 Model Optimization**

**3.5.1 Early Stopping and Hyperparameter Tuning**  
To prevent overfitting, early stopping was employed during the training phase. Hyperparameters such as learning rate, batch size, and the number of neurons in each layer were tuned using grid search to optimize the model’s performance.

**3.5.2 Cross-validation and Model Refinement**  
A 5-fold cross-validation approach was used to ensure the robustness of the model. This method splits the data into training and validation sets, rotating the splits to validate the model’s consistency across different data subsets.

**3.6 Model Evaluation**

**3.6.1 Accuracy, Precision, Recall, and F1-Score Metrics**  
The model’s performance was evaluated using accuracy, precision, recall, and F1-score metrics. The evaluation metrics revealed that the ANN performed well in predicting emoji-based sentiment, with notable improvements in sentiment detection when compared to baseline models.

**Classification report
**

**Table 3.1**

A diagram of data processing

Description automatically generated

**Figure 3.4**

**CHAPTER 4**

**IMPLEMENTATION**

**4. IMPLEMENTATION**

**4.1 Environment Setup**  
The project was implemented in Python, using libraries such as TensorFlow/Keras for building the neural network, pandas and NumPy for data manipulation, and matplotlib and seaborn for data visualization. The environment setup involved installing the required dependencies and setting up the appropriate Google Colab notebook configurations.

**4.2 Preprocessing, Model Training, and Evaluation Code**  
The code for data preprocessing included handling missing values, tokenization, and emoji cleaning. The model training section involved defining the ANN architecture, compiling the model, and fitting the data. The final section of the code focused on evaluating the model using the metrics described earlier.

**4.3 Dimensionality Reduction and Visualization Code**  
Dimensionality reduction techniques like PCA (Principal Component Analysis) were applied to reduce the number of features and improve model performance. Visualizations, such as emoji usage patterns by demographic groups, were generated to assist in interpreting the results.

**CHAPTER 5**

**EXPERIMENTATION**

**AND RESULT ANALYSIS**

### **5. EXPERIMMENTATION AND RESULT ANALYSIS**

### **5.1 Analysis of Emoji Usage by Demographics (Age, Gender)** Analysis revealed clear differences in emoji usage across age groups and genders. For example, younger users were more likely to use a wider variety of emojis, while older users tended to stick to conventional smileys. Gender differences were also significant, with women using more emojis related to emotion and support, while men used more object-related emojis.

### **5.2 Sentiment Variation across Platforms** The sentiment analysis showed that different platforms exhibited different emoji usage patterns. Social media platforms had a higher prevalence of neutral and negative sentiment emojis, while messaging apps showed more positive sentiment emojis, likely due to the more personal nature of conversations.

### **5.3 Performance Comparison of Neural Networks and Other Classifiers** The neural network outperformed other classifiers such as Support Vector Machines (SVM) and Random Forests in terms of accuracy and F1-score, particularly in classifying emojis with mixed sentiment. The ANN’s ability to handle complex patterns in the data gave it an edge over simpler models.

### **5.4 Outlier Detection and Emotional Response Discrepancies** Outlier detection revealed several cases where the sentiment expressed by emojis significantly diverged from the sentiment conveyed by the text. For instance, sarcastic emojis often accompanied negative text, creating a unique challenge for sentiment classifiers.

### **CHAPTER 6**

### **CONCLUSION**

**6. CONCLUSION**

The analysis of emoji usage across different demographics and platforms revealed significant patterns in sentiment expression. The neural network model demonstrated strong accuracy in predicting emoji-based sentiment, outperforming other classifiers in handling diverse contexts. Outlier detection highlighted discrepancies between expected and actual emotional responses. This study contributes to the growing understanding of virtual interactions and sentiment analysis, with potential applications in social media analytics and marketing.

**6.1 Key Findings**  
The study found that emoji usage is heavily influenced by demographic factors and platform context. The ANN model was able to accurately classify sentiment based on both emoji usage and text, outperforming traditional machine learning models in this domain. The relationship between emoji usage and sentiment is more nuanced than previously thought, with context playing a significant role.

**6.2 Future Work and Enhancements**  
Future work could involve incorporating a wider range of demographics, such as geographical location and cultural background, to better understand the global variation in emoji usage. Additionally, using more advanced deep learning models like transformers could further improve the accuracy of sentiment classification in complex datasets.

**CHAPTER 7**

**REFRENCES**

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