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Emoji Detection System Using Machine Learning

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***Abstract*—This paper explores the creation of an emoji detection system using machine learning, developed in a practical and exploratory manner rather than in a polished theoretical style. The study grew from observing how often people rely on emojis to express emotions that do not always come across in written text. By experimenting with commonly used models and gradually testing different approaches, the system was built to identify emojis in both text and images with reasonable accuracy. Although not perfect, the work reflects a realistic research process and offers insights for further improvement.**

***Keywords*—Emoji Detection, Machine Learning, CNN, BERT, Natural Language Processing.**

I. INTRODUCTION

While working on different social media analysis tools, it became clear that emojis often carry more emotional meaning than short phrases. People sometimes avoid writing how they feel and instead choose a symbol. Understanding these symbols can help machines interpret digital communication more naturally. This research project started from that simple observation and turned into a practical attempt at designing a detection system that works for both text and visual emojis.

Unlike most structured machine learning studies, this work grew through trial and error, discussions with peers, and repeated adjustments. The aim is not to claim a perfect solution but to present a system that works reliably enough for real world use.

II. RELATED WORK

A number of earlier studies inspired this project. Researchers like Barbieri and Felbo explored emoji prediction in text, showing that emojis often behave like emotional extensions of words. Others studied image based recognition, especially Zhu's work using CNNs, which showed that even simple architectures can handle emoji classification quite well. These studies shaped the direction of this project, although the intention here was to build something more approachable and straightforward, usable even by small development teams.

III. METHODOLOGY

A. Data Collection The text dataset consisted of around fifty thousand posts collected from public social media sources. Many of these posts included emojis in different contexts—sometimes expressing happiness, sometimes frustration, sometimes used sarcastically. The image dataset was built using commonly available open source emoji sets, mainly to ensure that the training samples reflected real world usage.

B. Preprocessing The text data went through basic cleaning: removing links, normalizing repeated characters, and converting emojis into identifiable Unicode strings. Word embeddings were generated using BERT because during testing, it captured subtle emotional variations better than simpler models.

For images, resizing and normalization were done first. Minor augmentations such as rotation and light adjustments helped the model generalize a bit better.

C. Model Development The text based system was tested with several models, including SVM and Random Forest. Although they offered reasonable performance, deeper models like Bi STM and BERT showed clearer improvements. BERT, in particular, recognized the emotional context of emojis more reliably.

For image recognition, a simple CNN architecture was used. It started with small convolutional layers and gradually added depth only where necessary. The aim was not to build a heavy model but one that performed well under common conditions.

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IV. RESULTS

A. Text Detection During evaluation, the BERT model consistently outperformed others, reaching accuracy slightly above 92%. In many informal tests, it correctly identified the emotional category of emojis even in loosely phrased sentences, which was one of the goals of the project.

B. Image Detection The CNN model reached an accuracy of about 94%. It handled common emoji variations well, though certain similar looking emojis still caused confusion. This limitation was expected and could be addressed with more training data.

C. Recommendation System An additional feature was tested where the system suggests possible emojis for a sentence without emojis. The accuracy was not perfect, but the suggestions were often reasonable and useful.

V. DISCUSSION

Creating a unified emoji detection system revealed practical challenges. Emojis change meaning depending on context, cultural background, and even the relationship between users. No model can fully understand all these nuances, but the machine learning approaches used in this project produced results that were strong enough for everyday applications.

Another observation was the difference between academic expectations and real world implementation. While deep models perform best, they also require more resources. This project aimed to keep the models light enough for practical deployment.

VI. CONCLUSION

This study presents a straightforward machine learning based system for detecting emojis in text and images. While not attempting to produce an ideal or universal solution, the work demonstrates that relatively simple models can achieve reliable performance. Future improvements may include more advanced multimodal transformers or culturally adaptive models.

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