International Journal of Computational and Experimental Science and ENgineering (IJCESEN)

Vol. 11-No.2 (2025) pp. 2177-2202
http://www.ijcesen.com

ISSN: 2149-9144

Research Article

A Review on Emoji Entry Prediction for Future Finance Market Analysis Using Convolutional Neural Network

PC Lakshmi Narayanan[1]*, Kishore Kunal[2], Veeramani Ganesan[3], Sudhakar Ganesan[4], Anitha Jaganathan[5], Vairavel Madeshwaren[6]

[1]Loyola Institute of Business Administration, Department of Finance, Loyola College, 600034, Chennai, India.
* **Corresponding Author Email:** lakshmi.narayanan@liba.edu - **ORCID:** 0009-0007-5687-9623

[2]Professor of Business Analytics, Loyola Institute of Business Administration, Chennai , 600034.Tamil Nadu , India
Email: kishore.kunal@liba.edu - **ORCID:** 0000-0003-4154-690X

[3]Department of Management and Business Administration, Jeppiaar Institute of Technology, Sriperumbudur. Pin 631604, Tamil Nadu, India.
Email: veeramani.g@jeppiaarinstitute.org.in **ORCID:** 0009 -0003 -2242 -2167

[4]Department of Computer Science and Engineering, Sri Sai Ranganathan Engineering College Coimbatore, Tamil Nadu, India.
Email: sudhakar@reccbe.ac.in **ORCID:** 0000-0002-1029-4888

[5]Department of Artificial Intelligence and Data Science, Panimalar Engineering College, Poonamallee, Chennai, Tamil Nadu 600123, India
Email: anitha@panimalar.ac.in **ORCID:** 0009-0002-7773-0469

[6]Dhanalakshmi Srinivasan College of Engineering, Coimbatore , 600034 Tamil Nadu , India
Email: phdannauniv2020@gmail.com - **ORCID:** 0000-0002-8687-7887

Article Info:

DOI: 10.22399/ijcesen.1490
Received : 22 January 2025
Accepted : 20 March 2025

Keywords :

Convolutional Neural Network,
Environment,
Emoji,
Sentiment Analyses,
Prediction.

Abstract:

Textual and financial data in social media has come a long way in the present. Emojis, the primary focus of this study piece, allow emotions to be visually represented thanks to the advent of text-based digital communication. By adding visual currency attractiveness to text, emojis in digital communication enhance communication and open up new channels for innovation and exchange. The neural network model for text-based emoji entry prediction is highly optimised, however because of little knowledge in this field, it is more difficult to predict future emojis from images all the finance symbols. Emojis are a great alternative to linguistically independent, sentiment-aligned embeddings since they are consistent and convey a clear sentiment signal NSE and BSE market. Compared to models for text, models for symbolic description have received less attention. In this study,Main researchers employed CNN architecture for image classification together with an emoji2vec embedding into the word2vec model to predict emoji from photos apply in finance sector and finding. Additionally, we performed a sentiment analysis on the text to forecast upcoming emoji labels added. Our approach effectively communicates how the emojis relate to one another. The length of the search for incoming image-based emoji predictions has been optimised using this model.

1. Introduction

Computer mediated communication (CMC) is becoming more and more ingrained in daily life due to the growing use of computers and technological advancements. Numerous benefits result from it, such as bolstering emotional communication, enhancing the continuity of individual communication, and improving relationship quality. Nonetheless, the communication process in CMC may be impacted by the absence of non-verbal clues including tone, gestures, and facial expressions. Communicators have developed novel non-verbal cues to overcome this issue, including the use of capitalization in place of yelling, numerous exclamation marks to indicate excitement, and emotion symbols to represent facial expressions [1]. These expressive symbols are highly appropriate for social media communication, compensating for the lack of non-verbal cues in CMC. Emoji, a collection of expression symbols, were created as a result. Emoji are being used in network communication more and more, and their applications are also growing more varied. They are closely associated with marketing, law, healthcare, and many other fields, in addition to possessing distinctive semantic and emotional characteristics. Emoji research has gained popularity in academia, and an increasing number of academics from disciplines like computer science, communication, marketing, and behavioural science are researching them [2]. This work explores the evolution and application of emoji, describes their linguistic and emotional characteristics, compiles the findings from emoji research across disciplines, and suggests areas for future investigation.

The popularity of EMOJI, which are tiny ideograms that represent objects, people, and scenes, has skyrocketed. They can now be found in a variety of locations, including social networking websites and all major mobile phone platforms. The Oxford English Dictionary states that the word "emoji" is a Japanese invention that means "pictogram," and it is made up of the letters "e" for "picture" and "moji" for "letter or character." The 176 pictograms that made up the first set of emoji were initially accessible to users of Japanese mobile phones. With 1,144 single emoji characters specified in Unicode 10.0 and many more defined through combinations of two or more emoji characters, the accessible range of ideograms has substantially increased over the past years. In this work, [3] addresses emoji as a modality that is connected to text and images but does not reside within them. The author explores the characteristics and difficulties of connecting various modalities to emoji, along with the potential that emoji offer for multimedia retrieval.

The multimedia community has a long history of identifying and benchmarking innovative modalities. It's critical to start by attempting to comprehend how newly discovered modalities relate to previously recognised information channels. Examining the cross-modal connections between the modality and other modalities is one technique to achieve this. This attempted to give understanding by predicting nonverbal head nods based on semantic understanding of the accompanying conversation transcript, after identifying them as an information-rich and ignored modality. Similar to emoji, new modalities can also arise from the development of new technologies; examples include 3D models and the rise of microblogging [4]. Despite their ancient origins, emoji are a contemporary technological development of ideograms. Technology advancements can often provide fresh perspectives on long-standing issues. One example is the use of infrared photography rather than natural photos for facial identification. Research progress can often be accelerated by presenting new tasks as challenges, as was the case with video concepts and acoustic scenes. Based on the history of multimedia challenge problems, we determine that emoji is a new modality that warrants a comparable analysis. We offer three emoji challenge tasks, state-of-the-art neural network baselines for them, and an assessment dataset in order to promote future emoji research.

Emojis are widely used, although not much research has been done on them. Most previous studies on emoji have been descriptive in nature, e.g., they have examined how emoji usage patterns vary across demographic groups [5] or have employed emojis as a signal to signify the emotional impact of accompanying media. The emphasis on sentiment is probably due to the abundance of "face emoji" (e.g.) that are intended to convey a certain feeling or response. Although the focus on these face emoji overlooks the hundreds of other emoji that are deserving of study on their own, these face emoji are by far the most noticeable and among the most commonly used emoji. In addition to these facial emoji, the entire emoji set includes a vast array of other items that might not have a strong sentimental signal, like foods , signs, and scenery. By concentrating only on the emotive subset of emoji, one is ignoring the possibilities and messages that the numerous other ideograms that are accessible convey.

In this work, we treat emoji as stand-alone, information-rich modalities. Emoji are frequently included in text, but we still see them as separate from text. Emojis can bring richness of meaning and variety of semantics that are not possible in pure text because of their visual aspect. Emoji can occasionally be used to merely substitute words in text, but more often than not, they add fresh information not found in the text alone [6]. Emoji can be used as an additional modality to add sentiment to a message, explain the intended meaning of an ambiguous message, or completely change the text's original meaning in ways that words cannot. Emojis are meaningful on their own and have compositionality, which enables multi-emoji statements to have more complex semantics.

Emoji are frequently utilised as a sort of visual humour when a specific symbol resembles something completely different. These characteristics, together with a cross-linguistic semantic resemblance [7], imply that emoji are different from their common textual companions even though they are Unicode characters. Emoji are different from regular images even though they are represented by tiny pictures. In contrast to images, where the details of a particular image are frequently more important than what it is representing generally (i.e., it is a photo of your dog, not just a photo representing the semantic notion of "dog"), the specifics of an individual representation in an ideogram are frequently incidental to the underlying meaning of the image as a form of symbology. The fact that emoji are only unicode characters serves as more evidence for this distinction. Emojis are characters, hence the specifics of their representations depend on the platform that supports them [8]. This means that different systems may have significantly different versions of a same emoji. These factors cause their conduct and meaning to diverge significantly from those of images.

2. Development Of Emoji

Smileys were the original source of emoji, which later developed into emoticons, emoji, and stickers in more modern times. Smileys are thought to have been the first expression symbols, having debuted in the 1960s. Printed on buttons, brooches, and t-shirts, Smiley is a yellow face with two dots for eyes and a big smile. This sign grew widely and became a recurring element of western popular culture by the early 1980s. Since its introduction in 1872, emojis have been used to portray various facial expressions using normal computer keyboard punctuation. They are a paralinguistic component that are frequently employed at the conclusion of sentences [9]. Before the invention of emoji, emoticons were a common tool used by Instant Messaging (IM) users. Similar to nonverbal cues in interpersonal communication, emoticons can be used to express emotions, clarify intentions in unclear situations, increase communication efficiency, and convey feelings [10].

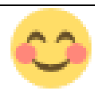
Additionally, emoticons have nonverbal communication purposes. They can provide delight, encourage interaction, and help individuals receiving them accurately comprehend the sender's emotion, attitude, and level of attention [11]. They can also help foster communal identification. Preferences for emoticon usage vary depending on gender and cultural background. Emoticons have also been proposed for practical use, e.g., in psychological testing, emotional monitoring, and sign design. Shigetaka Kurita, a Japanese designer, designed the first set of emoji, which were introduced in 1999. The Japanese term (e=picture) 文(mo=write) 字(ji=character) is transliterated as "emoji"[12]. These are graphic symbols with preset names and Unicode codes that can represent a variety of things, including animals, plants, activities, gestures/body parts, and objects, in addition to abstract notions, emotions, and sensations expressed through facial expressions. Emoji use can add additional emotional or contextual meaning to communication, improve the message's attractiveness to recipients, assist users in tone adjustment and conversation management, and play a part in managing and maintaining interpersonal relationships. Emoji use is associated with similar brain responses to face-to-face communication [13]. Emoji, being a visual language, facilitates the use of English-dominated social media platforms by non-English speaking countries.

Emojis are frequently used in email, social networking, instant messaging, and a variety of other CMC applications. Emoji, as shown, replace nonverbal clues in CMC to convey the meaning and feelings associated with information [14]. Stickers have been more popular in recent years as a means of improving the interpretation of information transmission and better expressing its meaning. Stickers can facilitate conversational fluidity by assisting users in dynamically and strategically selecting the most effective means of expressing their thoughts, feelings, and goals. In addition, stickers can serve strategic purposes such maintaining social status, managing impressions, building one's social presence, and self-presentation [15]. Additionally, a high degree of closeness can be established by replying to a partner using a combination of text and stickers. Emoji, stickers, emoticons, and smileys are varied in form and substance, and users have preferred them at different times [16].

Smileys can boost morale and promote good vibes; they are frequently used in commercials and product packaging. Unlike emoticons, stickers, and emoji, which are made up of an entire character set, a smiley is just one single symbol that is sporadically used in communication [17]. Emoticons can be utilised in CMC and display face expressions through different punctuation mark combinations. Research have revealed that while emoticons and smileys perceive information in the same way, smileys have a stronger effect on people's moods than emoticons that smile [18]. As an improved form of emoticons, emoji are now thought to be better than emoticons in terms of expressiveness, input speed, and information richness.

Emoji and emoticons serve the same purpose since they are both supplemental communication tools [19]. However, it has been demonstrated that the introduction of emoji has had some influence on the standing of emoticons. Users utilise emoji more often than emoticons, and they do so with a more upbeat attitude and a greater sense of identity [20]. Recently, stickers have become popular. Emojis rely on Unicode, which cannot be altered, and they are larger, have both static and animated forms, and may be added or removed. However, stickers cannot be included in text messages; they may only be delivered independently [21]. The distinctions between smileys, emoticons, emoji, and stickers are compiled in Table 1. This study primarily reviews and analyses related research on emoji because they now comprise the most commonly used and standardised symbolic language with the greatest number of studies already published [22].

Table 1. *The differences between smiley, emoticons, emoji, and stickers*

Form	Content	Usage Scenarios	Unicode	Examples
Static	Facial expressions, abstract concepts, emotions/feelings, animals, plants, activities, gestures/body parts, and objects	Daily life / CMC	Own unicode	
Static	Single smiley face	Daily life	Without unicode	
Static/Animated	Texts, facial expressions, abstract concepts, emotions/feelings, animals, plants, activities, gestures/body parts, and objects	Daily life / CMC	Without unicode	(Animated face)
Static	Various facial expressions	Daily life / CMC	Without unicode	

3. Emoji Use

Emoji is a common non-verbal indication in CMC used in online communication. Emoji make up almost half of all text messages on Instagram, with 5 billion of them being used on Facebook every day [23]. As of March 2019, there were 3,019 emoji in Unicode. Emoji's impact on online communication was demonstrated in 2015 when the Oxford English Dictionary designated it the word of the year.

3.1 Use of Inspiration

Emoji's ease of use, simplicity, and ability to facilitate emotional expression are what draw most users to them. Emoji can support people in developing their own identities, expressing themselves. Emoji are used in communication as contextualization cues. This involves establishing an emotional tone, decreasing discourse ambiguity, improving context appropriateness, and amplifying or weakening speech acts [24]. Emoji are also utilised as a greeting, as well as to preserve and improve social connections and improve communication on a platform. But according to other experts, emoji can also be used maliciously to convey false information.

3.2 Diversity in the Use of Emojis

Different interpretations while utilising emoji might result from variations in individual traits, platforms, cultural backgrounds, and settings. Additionally, emoji are utilised for certain issues, like situations that are sexually provocative [25]. This review paper provides a methodical overview of the variations among emoji in terms of user inefficiency and individual, cultural, and platform variability.

3.3 Individual diversity

Both personal psychological traits and demographic traits have an impact on the use of emoji. There are notable gender variances, to start. While men and women use more different forms of emoji, women use emoji more frequently and in a more positive way, despite the fact that both sexes comprehend the role of emoji similarly. This pattern, however, differs depending on the context of communication. Women are more likely than men to utilise emoji in public communication, whereas the opposite is true in private. When it comes to emoji cognition, women find them to be more recognisable, understandable, and significant. When expressing emotions, men tend to utilise the same emoji more often [26]. The recipients of the same emoji used by men and women experience distinct feelings. According to Butterworth et al. (2019), women are viewed as more appropriate and appealing when they send messages with loving emojis, whereas men are viewed as more appropriate and attractive when they send messages with less loving but friendly emojis.

The psychological variations among individuals also impact the use of emojis. According to research, there is a negative correlation between users' emotional distress and positive emoji use and a positive correlation between Facebook users' extraversion and self-monitoring traits and the frequency of emoji use. According to [27], an emoji-based personality test revealed that the Big-Five personality traits of agreeableness, extroversion, and emotional stability were connected with the similarity score between an emoji and the individual, but not with conscientiousness and openness. More specifically, good emoticons were positively connected with extraversion and negative emojis with emotional stability. Furthermore, agreeableness and blushing emojis (like,) had a positive correlation.

A few emoji forums have appeared as people's enthusiasm for utilising emoji grows. People converse with one another in the forum to explore the different meanings and applications of emoji. People are starting to build their own expressions and add more unique features to emoji instead of relying solely on the system's pre-existing emoji due to the growing desire to convey individual diversity. For example: . These are original symbols made by users by rearranging pre-existing emoji [28].

3.4. Cultural diversity

Emoji usage is shaped by social, linguistic, and cultural contexts in addition to cultural norms. It is also impacted by a variety of variables, including user group, living situation, language environment, and cultural background. Emoji usage is significantly impacted by cultural differences. Emoji usage patterns can vary greatly depending on one's cultural background. Users from Pakistan, India, and Finland, for instance, will utilise particular emojis based on their cultural practises [29]. According to Hofstede's cultural dimension model, when it comes to usage behaviour, individuals in nations with high levels of indulgence, power distance, and uncertainty avoidance tend to use more emojis that represent negative emotions, whereas individuals in nations with high levels of individualism, long-term orientation, and uncertainty avoidance tend to use more emojis that represent positive emotions [30].

In particular, users in China are more prone than users in Spain to communicate negative emotions through non-verbal signs like emoticons and emojis [31]. Additionally, studies have revealed that users of user-generated restaurant reviews websites from Hong Kong and the US use emojis differently, which may be a reflection of underlying cultural differences. Owing to the variances in emoji usage across cultures, an Emoji Grid reflecting proven cultural traits was constructed for cross-cultural study on emotions connected to food [32]. It is clear that there are differences not just between nations but even within one. The usage of emojis is impacted by several national development metrics, such as GDP per capita, trade, tax rates, and life expectancy [33]. Emoji use in the "first world" (defined here as North America, Western Europe, the Russian Federation, and Australia) is characterised by a lack of emotions, according to one line of research using the KMEANS clustering algorithm. In contrast, the "second world" cluster (which includes most of South America, Eastern Europe, India, China, Eastern Europe, Morocco, Algeria, and Tunisia) uses emoji in a more specific, emotionally clear manner. A combination of positive and negative emoji are used by the "third world" cluster (Angola, Nigeria, Sudan, Jordan, Saudi Arabia, Yemen, Pakistan, Nepal, and the Philippines) and primarily negative emoji are used by the "fourth world" cluster (certain African countries) [34].

The way that emojis are used also depends on the language context. Emoji exhibit a high degree of context sensitivity in cross-language communication, which means that their linguistic and textual environment greatly influences them [35].

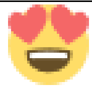
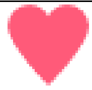
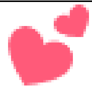
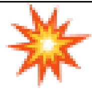
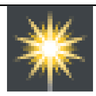
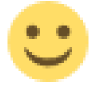
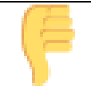
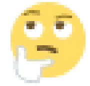
Figure 1. *Enviornment conscious Emoji*

Because they both speak English, for instance, study indicates that Britain and America use emojis quite similarly. However, when other languages like Italian and Spanish were compared, the similarities decreased [36].

3.5. Environment Queen's Climate Conscious Emoji Guide

This emoji is meant to be used deliberately in response to non-sustainable things. The ideal reply when someone offers you a straw made of plastic [37]. The envious heart emoji is intentionally used to symbolise leading a life that is plastic-free, low-waste, and has a minimal impact on the environment [38]. Evergreen trees assist to moderate rising temperatures by absorbing greenhouse gases from the atmosphere. Make a plea for the preservation of our rainforests by using the evergreen tree emoji!.
What constitutes an eco-friendly way of living! Use this emoji to put pressure on your friends to reduce, reuse, and recycle in order to combat global trash pollution! [39]. This gorgeous broccoli floret has higher protein content per calorie than steak! Make thoughtful use of broccoli to encourage a plant-based diet low in carbon footprint [40].
This emoji, also referred to as globe, is appropriate for use in any conversation on environmental preservation [41].
Known as a sprout or seedling, it is currently the global representation of the plant-based movement.
Diversity of platforms is one of the key elements influencing the use of emojis. Users' emoji preferences are influenced by the way emoji are presented on various operating systems and by the architectural features of various network platforms. Despite using Unicode, emoji are shown differently in iOS, Android, Microsoft, and other systems as a result of the impact of various developers (Table 2 and Figure 1). Emoji on the iOS platform are more visually appealing, recognisable, understandable, and significant than those on the Android platform, according to studies. When using emojis across platforms, there will be misunderstandings and differences in how they are interpreted emotionally and semantically due to this display disparity between the platforms [42]. Additionally, experts have examined several social media sites like Facebook, Instagram, and Twitter and discovered that each platform's users have distinct preferences when it comes to emoji usage. Emojis that are most popular on one platform might not be on others. On Facebook, for instance, people use emoji more frequently and in a more positive way than on Twitter. Some scholars, however, concentrate on less mainstream community platforms, such as Gab [43]. When faced with an identical incident, Gab users typically post positive emoji to convey irony in text that has negative overtones, but Twitter users typically use emoji to convey scepticism.

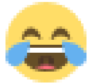
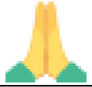
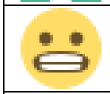
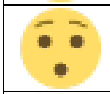
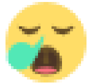
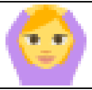
Table 2. *Emoji differences on major platforms*

	ANDROID	IOS	WINDOWS
Face with fears of joy			
Red heart			
Pleading face			
Fire			
Smile face			
thumbs			
thinking			

3.6 Use Inefficiency

Emojis can be useful for communicating emotions and understanding text meaning, but their use sometimes creates difficulties in communication, which hinders productivity. Despite the apparent similarities among emoji, their perception is subject to cultural context, technical variations, and unique visual attributes [44]. Users may interpret the same emoji differently depending on their intended meanings, which may differ from the official definitions (Table 3). The inability of the two parties to understand one another in this situation decreases the effectiveness of communication. According to [45], there are variations in how people interpret negative emoji. The sender and the recipient may have 26% different emotional responses to the same unpleasant emoji. There is a greater degree of misinterpretation of facial emoji than non-facial emoji, but both are correlated with the degree of information ambiguity. Because of variations in platform displays, people's interpretations of emoji when utilised across platforms will differ more in terms of their emotional and semantic meaning [46]. The disparity in interpretations of emoji causes communication inefficiencies, disrupts conversations, and shatters interpersonal bonds.

Table 3. *Common examples of emoji using ambiguity*

Emoji	Name	Misunderstanding	Official definition
	Confounded face	Confuse	Frustrated and sad face
	Dizzy	Being dizzy	Fantastic ideas
	Face with Steam From Nose	Imitation, anger, and contempt	Pride face
	Face with tears of joy	Something is funny or pleasing	A high five
	Folded hands	Please or thank you or praying hands	Loudly crying face
	Grimacing face	Nervousness, embarrassment, or awkwardness	Mischievous grimace
	Hushed face	Being hushed by concern or correction	Astonished face
	Ogre	Depicts an oni, a kind of hideous ogre in Japanese folklore	Supernatural or figurative beasts and demons
	Sad but relieved face	Concern or Anxiety	Crying Face
	Sleepy face	Tired or sleeping in anime or manga	Crying face
	Woman gesturing ok	"OK" sign	Put your hands together as a loving heart
	Women with Bunny Ears	An iteration of the Playboy Bunny known in Japan as a Bunny Girl	Friendship, Fun, or "Let's party"

3.7. Descriptive analysis of emoji usage.

Emoji for Sentiment:

The majority of earlier research has mostly considered emoji as a sentiment indicator. This is accomplished either overtly, by taking sentiment into account directly, or covertly, by taking into account just widely used emoji. Sentiment-laden emoji make up a disproportionate amount of the most popular emoji. Emojis with faces, thumbs up, and hearts are commonly used, although less emotive ones like objects, flags, and symbols are far less common. As a result, any research that solely takes into account the most widely used emoji may be biassed in favour of highly sentimental emoji [47].

The majority of earlier research has mostly considered emoji as a sentiment indicator. This is accomplished either overtly, by taking sentiment into account directly, or covertly, by taking into account just widely used emoji. Sentiment-laden emoji make up a disproportionate amount of the most popular emoji. Emojis with faces, thumbs up, and hearts are commonly used, although less emotive ones like objects, flags, and symbols are far less common. As a result, any research that solely takes into account the most widely used emoji may be biassed in favour of highly sentimental emoji [48].

An important study on emoji sentiment analysis that ranked the emotion of 751 emoji—the most common in their data—and annotated a set of tweets. Their research revealed that whilst certain emoji were highly correlated with positive mood, others were largely neutral and rarely linked to either strong beneficial or detrimental sentiment. In a similar vein, they noticed that certain emoji are commonly used to convey both very favourable and adverse feelings. These findings imply that it is incorrect to view emoji as only a simple way to express emotion and that there is a richer, more complex meaning behind emojis. Finally, some works view emoji as a pure sentiment indication, especially face emoji. Emojis are used as a source of input in the method by [49] to assess the tone of social media posts that reference specific brands.

Taking it a step further, considers emoji to be a trustworthy source of sentiment. They create a data set for sentiment forecasting and automatically label it with a collection of emoji. An method like this could result in noisy annotation because of the wide range of ambiguity in utilisation and the sentiment difference between text and emoji that has been studied in earlier research [50].

Analysis of Emoji Usage:

Several studies have contributed to our understanding of the characteristics and patterns of emoji usage in everyday life. Many studies have examined the ways in which various nations and cultures use emojis differently. In the meanwhile, it examines how gender variations in emoji use manifest themselves. Emoji usage is increasing worldwide, despite variations in how different groups may utilise them. This is demonstrated by the data. Emoji share semantic characteristics that are orthogonal to the communities in which they are used, and they are not restricted to any one language or culture, which further supports our notion that they represent their own modality [51]. The issue of ambiguity in the interpretation of emoji is examined in a number of works. Emoji are often found to have some degree of ambiguity, and the type of image that a given platform chooses to utilise can exacerbate this uncertainty. Interestingly, it notes that adding a second input modality—textual context—significantly enhances the meaning's distinctiveness. This discovery is consistent with the long-standing knowledge within the multimedia sector that using multiple modalities might enhance prediction [52]. Research has also looked into the ambiguity that exists between the author's intended meaning and readers' interpretations of messages containing emojis [53]. Emojis are a hard modality for algorithmic interpretation, worthy of pursuit, and with a high ceiling for perfection due to their ambiguity and wide range of possible meanings. Emoji relationships with one another have been researched [54]. Numerous authors' works provide a comprehensive investigation of how emojis are used and suggest a methodology for determining how connected two sets of emojis are. In a similar vein, it examines the challenge of determining which text tokens are most closely associated with a specific emoji. In order to achieve this, the authors use a skip-gram model to develop a shared embedding space. They then use this mutual semantic space to discover text tokens that are most similar to the emoji. Both [55] and [56] concentrate on descriptive study of emoji usage, even though they both learn models that may be used for emoji prediction.

In a similar vein, recent research has focused on determining the many contexts in which text can incorporate emoji. Emoji are used in [57,58], and [59] either as a direct substitute for text or as an additional element that improves or modifies the text's meaning. The project builds a dataset of 4100 tweets that were marked to show whether or not redundant data (data that is already included in the text) is contained in the emojis. In their set of annotated tweets, they discovered that the non-redundant class of emojis was the largest one. This finding validates our theory that emoji are separate from any accompanying text, even though they are intertwined with it. While research has focused on developing models based on real-world usage data to address the issue of comprehending emoji usage, other efforts have attempted to develop an understanding of emoji usage through more manual means. For instance, by merging multiple user-defined emoji meaning databases, obtains a structured understanding of emoji usage. Subsequently, their study leverages this data to construct a sentiment analysis model that outperforms models trained directly on real-world usage data. This type of pre-defined, organised knowledge of emoji is comparable to the no-example method that we have previously [8] and are now exploring further in this work. But rather than focusing just on using emoji as a tool for sentiment analysis, this effort aims to use them as a rich, informational modality. An early study on the compositionality of emoji can be found in.

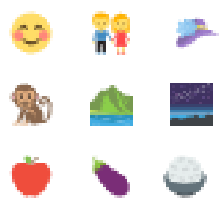
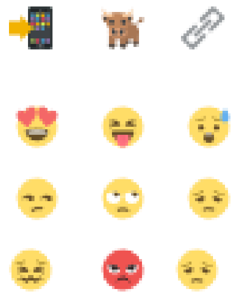
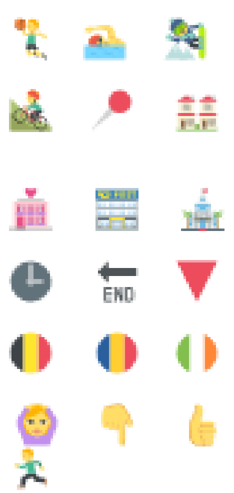
3.8 Functions Of Emoji

Emojis are a crucial visual symbol in computer-mediated communication that are used to convey a wide range of material, such as people, animals, food, and activities. Emojis have a semantic role in which they can be utilised as a non-verbal cue or as a language unto themselves. Emojis additionally serve emotional purposes (table 4).

The Emotional Functions of Emoji

Emoji are a vital tool for online connection and emotional communication since they are nonverbal signs with deep emotional connotations. Emotions can be enhanced or expressed with emojis. After examining 33 face emojis, it discovered that the majority of them could convey one or more emotions. Emojis have a deep emotional significance, which makes them an important subject for researchers studying emotions and creating emoji emotional lexicons. [60] used artificial annotation to categorise emojis as positive, negative, or neutral based on how they expressed

Table 4. *Categories, semantic, and emotional functions of emoji.*

	Category	Definition	Example
Content	• Smileys and people • Animals and nature • Food and drink	• Emojis for smileys, people, families, hand gestures, clothing, and accessories. • Emojs for animals, nature, and weather. • Emojis for fruit, vegetables, meals, beverages, and utensils	
Emotion	• Non-behavioral • Positive • Neutral • Negative	• Represent objects, symbols, animals etc. • Express positive emotions such as happiness, joy, excitement, etc. • Express moderate emotions. Neither positive nor negative. • Express negative emotions such as sadness, anger, being upset, etc.	
Meaning	• Activity • Travel and places • Objects • Symbols • Flags • Behavioral	• Emojis for sports, music, the arts, hobbies, and other activities. • Emojis for varied scenes, locations, buildings, and modes of transport. • Emojs for household items, celebrations, stationery, and miscellaneous objects. • Heart emojis, clocks, arrows, signs, and shapes. • Flag emojis, mainly flag emojis of different countries. • Express a behavior, behavioral intentions or activities, such as agree, • running, etc.	

emotions. They discovered that while most emojis were positive, some could also be used to convey satire or sarcasm.

Owing to the subjectivity involved in human annotation, several scholars have suggested creating emoji lexicons automatically. Using the official definitions found in emojipedia, it automatically created an emoji lexicon.

Emoji are frequently used in online communication to express emotions due to their deep emotional implications. Emoji are generally used more in happy messages and less in depressing or irate ones. People's attention spans and reactions are influenced differently by different emoji. Facial emoji perform better than non-facial emoji, despite the fact that both can convey emotions. Non-facial emoji can evoke happy feelings, such as joy, but they are unable to alter the message's emotional tone.

The Semantic Function of Emoji

Emoji are used in communication to transmit semantic concepts in addition to emotions. They can serve as nonverbal indicators to aid in deciphering the general meaning of CMC messages. The possibility that emoji will one day stand alone as a language has been the subject of extensive debate. Furthermore, because emoji semantics are both diverse and similar, a lot of computing researchers focus on the emoji word sense disambiguation task. According to several studies, emoji have their own language. They can represent meanings as an independent expressive modality, have a semantic function and a visual rhetoric function, and can express finer semantics by combining distinct emoji. Emojis have a deeper semantic meaning than plain text and exhibit cross-linguistic semantic similarities. In order to investigate the prospect of "emoji-first" communication, the social media app Opico was developed at the application level. This demonstrated that emojis can be used independently in conversation without the requirement for text [61].

Emoji, according to some scholars, cannot be utilised as a stand-alone language. Emoji were discovered to be comparable to Chinese character radicals. It makes the case that emoticons are basically a type of visual paralanguage. Emoji are also rarely used on their own and are typically employed in textual contexts. Emoji must be incorporated into the text in order for it to have a complete meaning and to increase the text's credibility and clarity. Emoji is often used as an addition to text, which further supports the idea that it is a paralanguage. Emojis have many meanings depending on the circumstance. When used, their variety of semantics and interpretive flexibility could cause ambiguity. As a result, the word sense disambiguation problem of emoji is the subject of many research. It has created an Emojinet that removes ambiguity by fusing text and emoji.

3.9. Research methods

Emoji Prediction for facebook data and different tweets

The use of emojis is growing quickly, but they should be easier to use. While there exist methods and data for non-emoji (text) content classification and prediction, none are accessible for emoji submission. Several methods have been proposed to predict future emoji entries from text, such as tweets and other text, but not from images, using similarity modelling and skip-gram models. The initiative uses images to anticipate the label for the next emoji addition. The technique recommends CNN for image classification and W2V for word vector representations. Furthermore, this method compares the similarity of emojis using Euclidian distance, and it represents the similarity of pictures using Cosine similarity. Emoji similarity is displayed using T-SNE plots (table 5). Furthermore, text sentiment analysis is carried out in order to forecast future emoji inputs using RNN [62]. Emojis have grown to be an essential tool for expressing emotions and improving communication. The study of emojis in relation to sentiment analysis and text comprehension is highlighted in figure 2. It proposes an unsupervised paradigm for sentiment categorization by integrating emoticon signals. The suitability of an emoji training heuristic for multi-class sentiment analysis on Twitter is evaluated using a Multinomial Naive Bayes Classifier.

3.10. Framework for Predicting Future Emoji Entries From Pictures

Emojis have grown to be an essential tool for expressing emotions and improving communication. The study of emojis in relation to sentiment analysis and text comprehension is highlighted. It proposes an unsupervised framework for categorising feelings by integrating emoticon signals (figure 3). The suitability of an emoji training heuristic for multi-class sentiment analysis on Twitter is evaluated using a Multinomial Naive Bayes Classifier [63].

System Optimization

Emoji have contributed to the enhancement of computer hardware and software performance. Emoji, for instance, can be utilised to create a variety of in-car interface designs. Researchers propose that the driver can improve mutual understanding between the driver and backseat passenger by using emojis and other features to feed back the emotions of the passengers, thereby optimising the functions of the central rear-view mirror [64]. Emoji can also be used in the field of password security, in addition. It developed the EmojiAuth project to investigate how including emoji into passwords impacts user experience and the accessibility of mobile authentication. Emoji-based authentication is a useful substitute for conventional PIN authentication because it is simpler to memorise than the Standard PIN (Personal Identification Number) input.

Modality Transitions

Emojis are a distinct expressive modality from text and images due to their visual characteristics and Unicode foundation. The conversion of emoji to other modalities, like text, picture, and video, is a topic of much research. Emoji2Video, for instance, provides an emoji-based method of searching for videos. Subsequent studies have concentrated on the transition from other modalities to emoji. It suggested two distinct methods to predict emoji based on text because of the relationship between users' choices of emoji and the emotional categories found in the text.

Communication

Emoji study in communication primarily focuses on two areas: first, the emotional and linguistic roles of emoji in context-mediated communication (CMC); second, the ways in which users' preferences for using emoji are influenced by several factors, including personal traits, cultural background, and system platform. Emoji serve as a substitute for non-verbal cues in CMC and are useful in communicating emotion, semantics, and fostering interpersonal communication. For instance [65], it

Table 5. *Emoji usage in different language tweets*

Language	English	Telugu	Hindi	Spanish
😍	17.1	22.7	9.7	9.7
😡	4.9	0.3	2.8	2.7
😱	3.8	3.9	4.9	6.3
👍	4.7	10.8	9.5	6.5
👗	15.3	5.7	6.8	10.8
🎩	2.6	0.5	2.6	2
🐢	3.5	1.6	2.9	3.4
🌳	3.3	0.9	4.3	6.1
☘️	3.2	13.4	9.4	4
🌼	3.1	5.1	8.6	4.6
⭐	3.6	3	6.7	6
☔	3	6.7	7.7	5.4
🍿	2.7	0.9	2.3	3.4
🎾	2.7	2.3	1.9	2.8
🚌	2.8	4.2	7.2	3.4
🏰	3.7	0.3	1.5	6.8
💛	10	16.6	7.5	13.1
➕	5.7	1.4	3.9	3.1

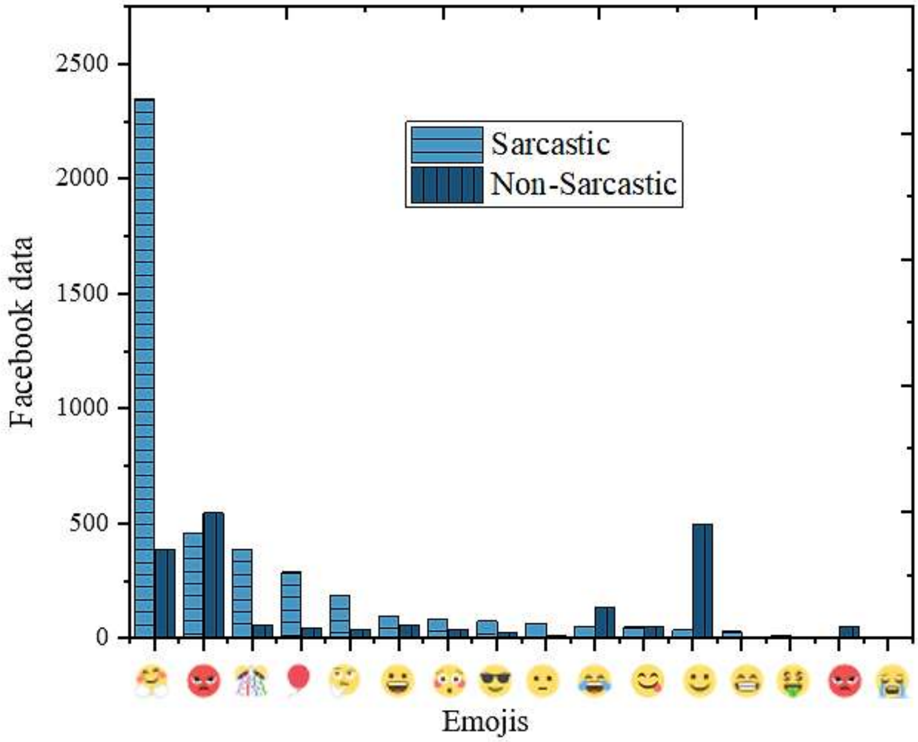


Figure. 2. *Comparison of top Emojis for Facebook data.*

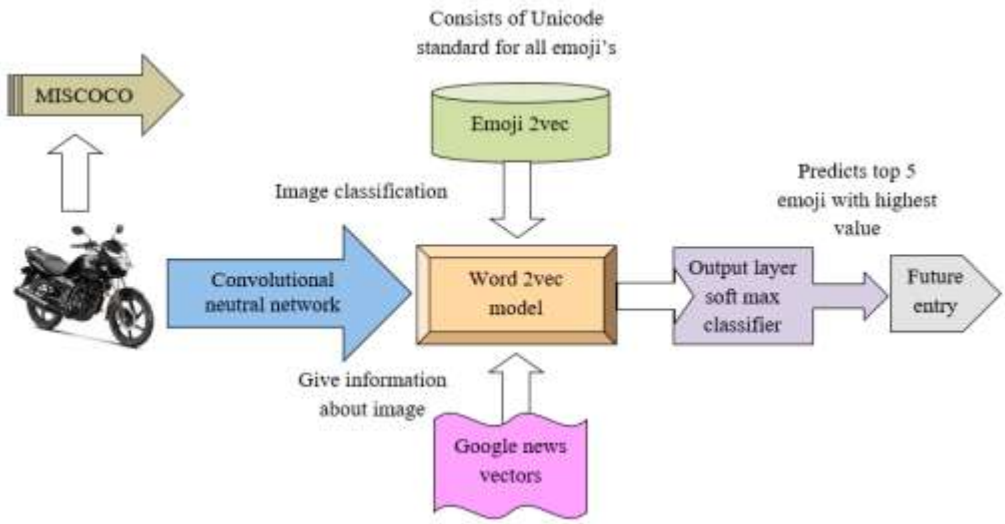


Figure 3. *A general framework for predicting future emoji entries from photos*

examined the emotional qualities conveyed by 33 different facial emojis and discovered that the majority of them had one or more emotional connotations. Emojis were categorised as positive, neutral, or negative based on how they expressed emotions, and it was discovered that the majority of emojis represented happy feelings. Emoji usage is higher in positive messages than in negative ones, according to similar studies. Emoji are incredibly adept at communicating emotions, both facial and nonfacial. Simultaneously, the interpretations of emotional expression can be enhanced by varying the emoji pairings. it investigated how the use of various emoji combinations affects feelings. The paper's section on the emotional functions of emojis includes references to other study in this field.

Demographic characteristics

A multitude of factors influence how each individual uses emoji. Three areas can be used to group the current research: system platform, cultural backdrop, and individual characteristics. First, demographic factors like user age and gender have a big impact on how emoji are used. Men use them in greater quantities than women do. Women use them more regularly. Emoji usage is higher among women in public communications but lower in private correspondence. Emoji with stronger emotional connotations are deemed more suitable and attractive for women than for men in terms of social cognition, whilst emoji with softer emotional meanings but friendlier meanings are deemed more suited for males. Second, the user's cultural background has a big influence on how they use emoji. Users from various nations will employ emoji that have particular ethnic or national connotations. Emoji designers in Finland introduce "sauna," Hindus use "Happy Diwali," and Pakistanis utilise the Namaz symbol. Emoji usage varies widely among users in different nations. Emoji and emoticons are used by Chinese people more than by Spanish people. Emoji are highly contextually sensitive, and their use varies depending on the type of language. For instance, using emoji. The data indicates a robust association between English-speaking nations and a weaker correlation with other language groups. Finally, variations in the way emojis are used also originate from variations in system platforms. Despite the Unicode support for emoji in operating systems, users display emoji differently in Microsoft, iOS, and Android due to limitations in these apps' developing compatibility. Emoji usage patterns vary throughout social networking sites, including Facebook, Instagram, Gab, Twitter, and Facebook. Emoji, for instance, are used more frequently and favourably on Twitter than on Facebook. Positive emoji are frequently used by Gab users to convey negative [66].

Linguistics

The pragmatic purposes of emoji and the potential for them to stand alone as a language are the subjects of linguistics research. Emoji have been found to have semantic qualities. They can be utilised as a paralanguage component or as a standalone linguistic, giving users a way to communicate and encouraging interaction and speech acts [67]. Regarding whether emoji can stand alone as a language, there are advantages and disadvantages. According to some scholars, emoji can independently convey meaning since they have more nuanced semantics, visual rhetoric, and text functions. There are researchers who disagree, arguing that emojis cannot be considered a separate language because their meaning is mostly dependent on the text around them. Emojis can only fully express semantics when paired with text.

Promotion

Emojis are suitable for use in marketing campaigns because of their emotive and visual qualities. Emoji are crucial for drawing attention, promoting social connections, improving customer satisfaction, and increasing purchase intent [68]. Therefore, it should come as no surprise that emoji are widely utilised in communications with customers state that emoji are also utilised to represent the feelings of customers. They are a useful instrument for measuring users' emotions because of their predominance in emotional expression. Emoji and emoticons are examples of textual paralanguages that can affect consumers' behaviour and cognitive processes in marketing-related contexts. For instance, emoji on food packaging can affect children's dietary decisions. Emojis have been shown to increase the persuasiveness, appeal, originality, and inventiveness of marketing campaigns. More young people are drawn to online marketing after emoji were introduced [69]. In order to, emoji can also be used to describe user profiles, reflect customer emotions, and track user sentiment towards particular goods, services, and brands. According to research, consumers' capacity to describe and distinguish stimuli using emoji is unaffected by factors such as gender, age, or frequency of usage [70]. In fact, some emojis may even assist consumers distinguish between product samples more effectively. Furthermore, emoticons and emoji are thought to be easy and natural ways to convey feelings connected to eating. However, other researchers note that despite emoji's greater simplicity and discriminability in emotional evaluation when compared to emotional language, its many interpretations may make the survey more difficult to administer. Emoji surveys therefore cannot completely replace the current text-based versions of attitude surveys. However, they can serve to enhance the existing shape.

Perspective

Two key features are the focus of studies in this topic. The first examines the connection between a person's use of emoji and their psychological traits, while the second looks at how emoji were incorporated into the design of the scale and how new psychological assessment instruments were put into use. Emoji use has been linked to a number of psychological characteristics, including emotional stress, self-monitoring, the big five personality traits, and others. Emoji use, for instance, is correlated with emotional stability, agreeableness, and extroversion among the big five personality traits, but not with conscientiousness and openness, according to research [71]. Simultaneously, certain research has endeavoured to incorporate emoticons into psychometric assessments.

Behavioural Sciences

Emoji study in behavioural science emphasises on three dimensions: preference, motivation, and influencing factors. A lot of research has been done on the reasons people use emojis. Emoji are used in interpersonal communication for a variety of purposes, including self-expression, managing and maintaining interpersonal relationships, creating personal identities, and facilitating and enhancing interaction [72]. Emoji, as a contextual cue, can assist users in establishing an emotional tone, reducing semantic ambiguity, and enhancing appropriateness in relation to context. The preference for using emojis has two components. The first is the choosing of emoji content by users, and the second is the extent to which emoji emotions correspond with actual sentiments. For instance, users from various nations add characteristics that are emblematic of their nations to emoji; users of a certain social media platform favour using optimistic emoji to convey irony in negative texts.

Health Care

Emoji research in the fields of public health and medicine mostly focuses on enhancing communication between doctors and patients as well as addressing personal behaviour. Emoji can be used to influence people's health-related behaviour, and research has demonstrated that doing so can strengthen good hand hygiene monitoring behaviour. Emoji usage can also strengthen patient-doctor communication and patients' capacity to take care of their own health. According to some experts, creating a collection of emoji expressly for use in patient care could improve patients' comprehension and ability to express the difficulties they have when managing their health [73]. Emojis' potency in expressing emotions makes them useful for identifying and forecasting mental health issues. Emoji have been incorporated into the depression assessment process and they discovered a considerable improvement in the accuracy of recognising depression.

Education

Emoji's effect on learning efficiency is the subject of much research in the realm of education. Emoji use in the classroom has been shown to improve students' comprehension of the material being covered, particularly in computer-mediated instruction (online learning). Emoji can enhance young children's capacity for self-expression and aid in their understanding of abstract ideas like emotions, interpersonal management, and security [74].

3.11 Network Model For Prediction Of Emoji

Convolutional Neural Network

COCO images are used as the input layer in ConvNets, a sort of convolutional neural network design. Convent-associated neurons have learnt weights and biases. ConvNet layers have neurons arranged in three dimensions: width, height, and depth, as opposed to a typical neural network. The four key layers of the ConvNet architecture are the convolutional layer, normalisation layer, pooling layer, and ReLU layer, as shown in Figure 4. The CNN output layer known as the Max Pooling layer describes images based on image IDs from the COCO dataset. Each sequential layer in this model consists of four core CNN layers, with the last sequential layer being an average pooling layer as opposed to a maximum pooling layer. The convolutional layer includes a convolutional filter that uses the inputs to produce a feature map. The ReLU layer applies a maximum function to all values in the input volume. The max pooling layer uses the greatest value from each neural cluster from the previous layer. The CNN-obtained image descriptors are sent into the W2V model. The Word2Vec is a three-layer neural network model with a single hidden layer. Word-to-language context (W2V) generates word embeddings for the given data.

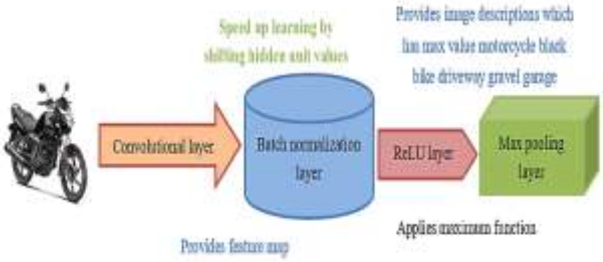


***Figure 4**. Convolutional neural network*

Embedding Network Smiley

Given the size of the collected dataset, deep neural network architectures can be used to efficiently learn the emoji embedding with reduced risks of overfitting the data. Our formal goal is to learn an embedding function, f, that maps an image, x Xdx, to an embedding, e Ede, or f: Xdx Ede. so that the image and emoji spaces' corresponding dimensions are de and dx. Using the proxy task of explicit emoji prediction, it is feasible to build f (Figure 5). When compared to other techniques, such metric learning in the emoji space, this has two key advantages. Consequently, it can now evaluate the embedding and create a novel zero-shot task for visual sentiment learning.

3.12 Recurrent Neural Network

RNN information is self-repeating. Both the current input and the information stored in memory from earlier inputs are used to inform judgements. Our model uses GloVe vector embeddings to train the

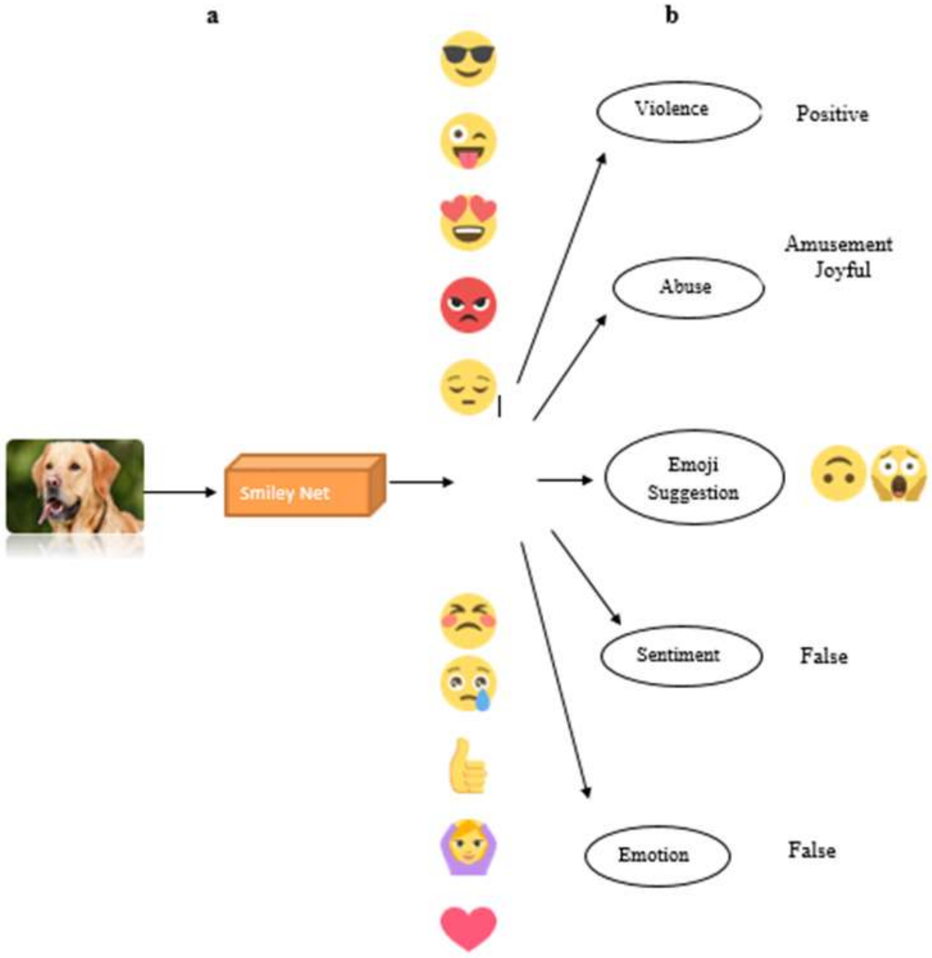


Figure 5. *(a) learns how to include photos in emoji's low-dimensional space. Transfer learning (b) can then be used to take advantage of this embedding for a variety of target tasks where it is necessary to derive emotions from visual data, including sentiment and emotion analysis.*

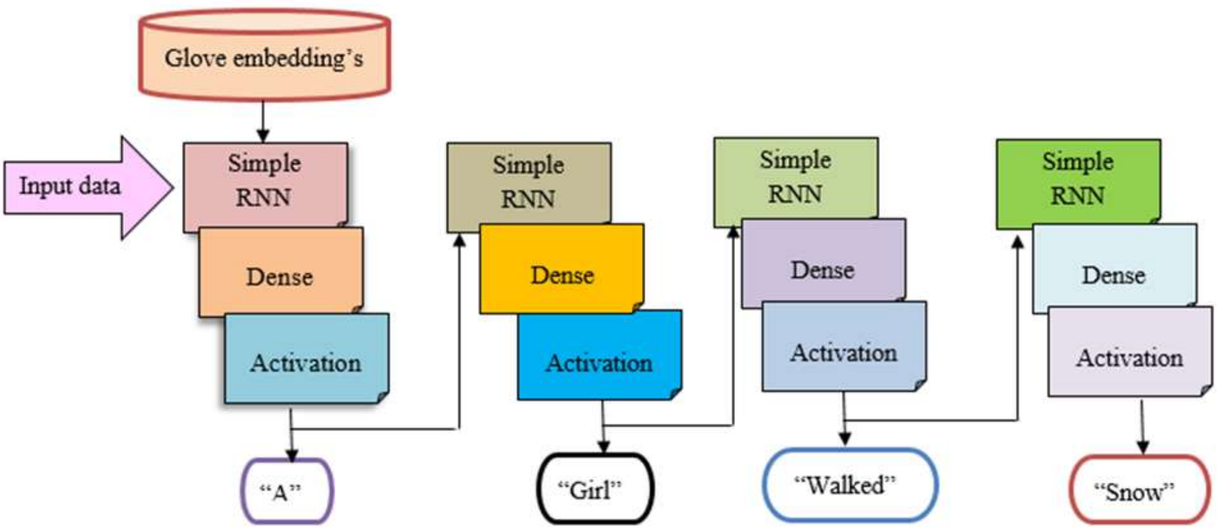


Figure 6. *Recurrent neural network*

text sentiment analysis on the textual data. Global Vectors is the basis for the distributed word representation method known as GloVe. Glove embeddings and the input data are utilised to train the network model [75]. A basic RNN layer is the foundation of an RNN, and layers for density, dropout, and activation come after. The simple RNN layer uses the input data's embedding matrix to build the space's output dimensionality unit. The dense layer increases the representational capacity of the network. The dropout layer prevents overfitting of the data. The activation layer creates probability for every word in the vocabulary using softmax activation. The most likely words are generated in Python and then mapped to the appropriate Unicode character to create an emoji name. The RNN architecture for the sentiment analysis of the text is shown in Figure 6.

3.13 Sample Availability

Several social media platforms, such Instagram, Flickr, and Twitter, constitute a large source of detailed emoji data. Emojis are utilised in over half of Instagram posts and are believed to be sent more than 700 million times on Facebook each day. Here, we choose our Twitter samples in a way that only contains tweets with emojis and tweets that are related to at least one image. The impetus for this stemmed from the fact that these aspects frequently operate as key context indicators that go beyond the visual information connected with the chosen emoji. By applying the previously described standards, the 2.8 million Tweets from the initial half of 2018 were identified. Figure 7 a-b

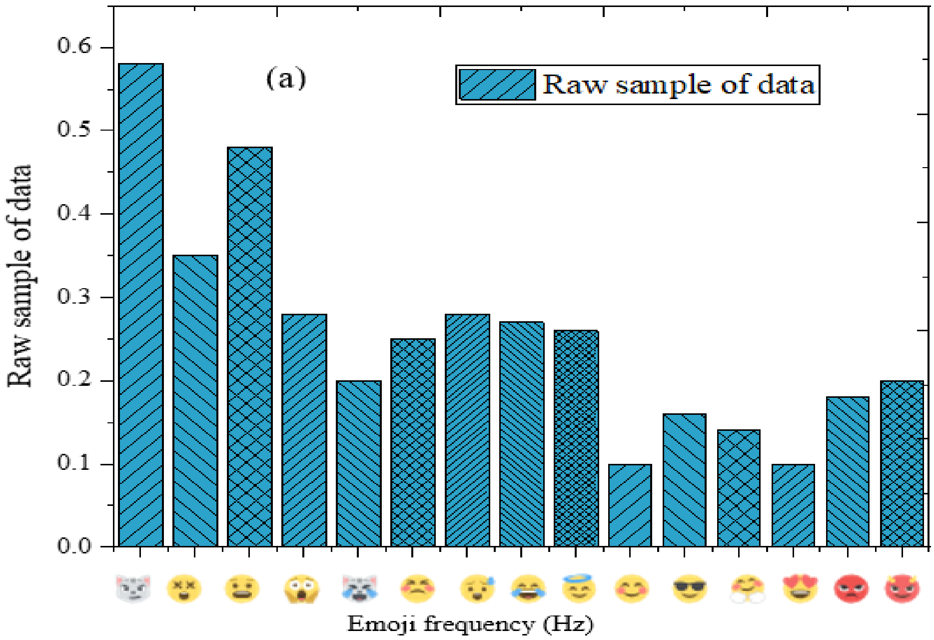


Figure 7a. *Emoji frequency in the*

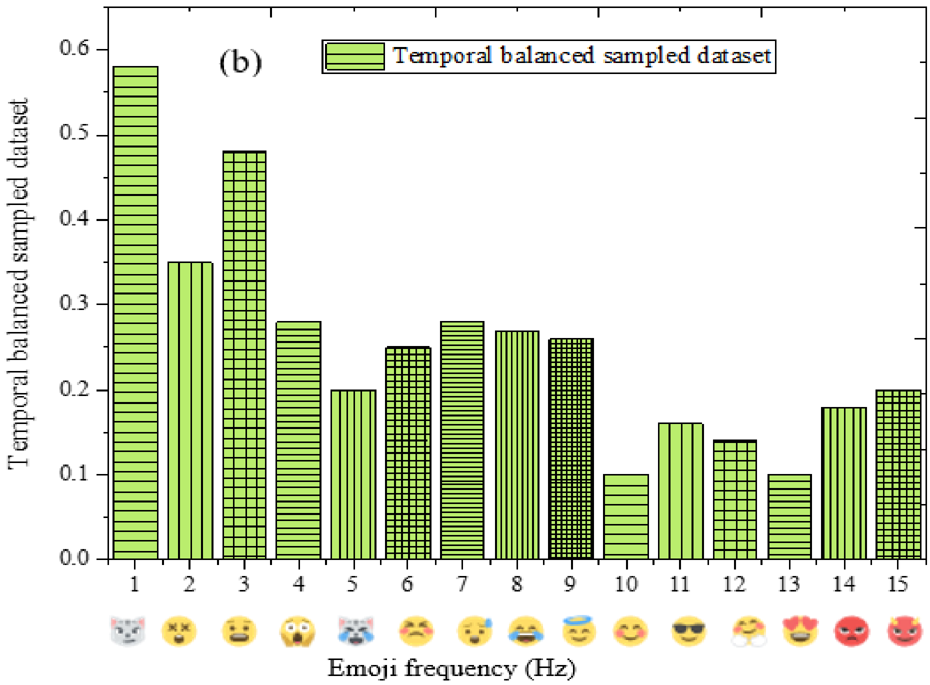


Figure 7b. *temporally balanced sampled dataset and a raw sample of data. The study makes use of dataset.*

() shows the label distribution of the data. The data exhibits a notable bias towards a limited number of categories and a long tail distribution; around 40% of the gathered samples consist of the top 5 most popular emojis. This poses a serious problem to most traditional machine learning methods, since an imbalanced training dataset might lead the learning process to anticipate the most frequent labels instead of finding a more informative representation. Furthermore, we see that when data are collected over a short period of time, the content of samples tends to be substantially biassed towards a limited number of major temporal events.

Image Preprocessing

Data preparation is an essential part of the process since irrelevant data, noisy data, and untrustworthy data might yield erroneous conclusions during the training phase of data mining. Preprocessing the data is therefore necessary before training. Because of the uneven dimensionality of the photos, each image in the data collection has to be scaled to have the same dimensions. ANTIALIAS is used by the Python Imaging Library (PIL) to automatically resize all images to 256256 pixels. We utilised the MSCOCO 2017 dataset (cocodataset.org) for image inputs, which consists of 15,000 training and 5,000 testing images. Using Google-News-vectors (GoogleNews-vectors-negative300.bin.gz), word vector representations are created [76].

Temporal Data Collection

In order to counteract content uniformity, this advises consistently selecting the tweets from narrower temporal windows while getting the data from a relatively lengthy period of time. Specifically, we collect tweets from January 1, 2016, to July 31, 2018. We separated the period into consecutive 30-day time intervals. To alleviate the label imbalance even further, we randomly select up to 4,000 tweets from each window's emoji categories. Furthermore, legitimate samples may contain up to five emojis, so some samples may have more than one label. In total, 4 million images and 5.2 million emoji labels were generated by this technique. Figure 6b shows the label distribution of the sampled dataset. As we can see, compared to the raw data distribution, our dataset has a more uniform distribution across the various categories. To have a better understanding of the relationship between labels, we generate a normalised correlation matrix of all the emojis in the collected data2. The association matrix shows that the two most widely used emojis, and, occur with most of the categories. In addition, the correlation matrix finds other semantically related categories, such as [] and [].

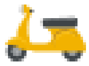
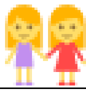
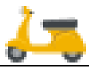
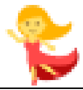
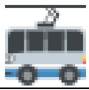
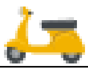
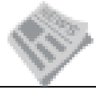
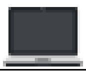
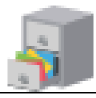
W2v Model

Word2Vec, another neural network model, uses CNN's image information to forecast future emoji entries. Emoji2vec, an emoji vector space model, is used in place of words for this assignment. Emoji embedding E2V uses the uniform Unicode representation of every emoji. W2V, which is based on E2V, offered a semantically effective paradigm for connecting text from CNN to emoji characters. W2V was created with the assistance of Gensim and NLTK. The word vectors used for training are the three million 300-dimension word vectors from Google News. W2V uses a Part-of-speech tag for each piece of information (e.g., noun, adjective, verb, etc.) that NLTK extracted from CNN about the given image. NLTK selects the appropriate nouns, adjectives, and verbs because these words—not any other words in sentences—make up the information required about a picture. To vectorize the remaining words in the textual data, Gensim employs word2vec. W2V extracts five emojis for each word in the CNN textual data that are either similar to or closest to the original word. With a word from CNN's textual data as the input layer, W2V is a three-layer neural network model. Each unique word in the Google News dataset is represented as a column in the matrix containing hidden weights that holds the word vectors in the hidden layer. The output layer is a multi-class classifier known as a Soft max regression classifier. Resized images are fed into the CNN model after being preprocessed into 256256 pixels. A specific type of neural network known as a CNN is made up of neurons that have teachable weights and biases. CNN is a multiclass image classifier with numerous labels and classifications. In terms of implementation, CNN was created using Pytorch. The max-pooling layer, the ReLU activation layer, the convolutional layer, and the batch normalisation layer are the sequential layers that comprise the CNN network architecture [77]. The CNN Convolutional layer converts the input images into a feature map using the convolution filter. The element-wise matrix multiplication and total are computed by swiping the filter across the input at each pixel location. The feature map displays the total. In the subsequent layer, known as Batch Normalisation, the inputs from the feature map are normalised by shifting the hidden unit values, accounting for the batch mean, and dividing by the standard deviation. This expedites the process of training and learning. Every value in the input volume is subjected to the maximum function of the ReLU layer. Each negative activation is converted to a zero value. This improves both the nonlinear properties of the model and the overall nonlinear properties of the network. Every layer that comes after another is a sequence of layers.

Conceptual Model

All of the images underwent preprocessing to eliminate any irregular dimensions. CNN finds it difficult to analyse different-sized photos. Hence, 256256 is the default dimension for all images used in prediction. After input picture preprocessing, the scaled image is sent to CNN for image classification [78]. CNN classifies the image using training data and outputs comprehensive textual information. Emojis that are similar to one another can be found and their degree of similarity can be calculated using the Euclidian distance measure. This makes it easier to forecast and analyse the forthcoming emoji labels with accuracy. An example of the emoji Euclidian distance measuring findings is shown in Table 6.

Table 6. *Euclidian distance measure of emojis*

Emoji 1	Emoji 2	Euclidean measure
		3.0394
		5.9283
		5.9348
		6.2304
		7.2352
		8.0934
		9.2323
		12.4958

Emojis are visualised using the TSNE plot in order to analyse their associations and find clusters of related emojis using a similarity score. TSNE does a pretty good job of capturing the local structure, and the clustered data is also extremely distinct. The similarity between two photos is measured using the Cosine Similarity metric. The cosine similarity metric is used because it employs categories as opposed to just two variables. The cosine similarity between the images is shown in Table 7. This model analyses the sentiment or emotions in the text to predict future emoji input labels. Five categories—joyous, in love, furious, sports, and eating—are used to group all of the written material.

An illustration of the degree of similarity between the two images may be found in Figure 8. photographs that are dissimilar show a high difference in the similarity values, whereas photographs that are comparable show a low distance value. Sentiment analysis is employed in Recurrent Neural Networks to predict future emoji entries [79]. This model stores in its memory both

Table 7. *Cosine similarity between images*

Image 1	Image 2	Score 1	Score 2	Cosine measure
		2.934857 3.938567 8.029348 9.938572 21.230948	6.233094 6.123311 5.231522 9.039863 2.213454	0.98
		21.984489 14.239480 11.349892 23.234121 3.029348	6.3509234 5.3059832 7.3458923 11.345903 5.2341155	0.94
		3.325896 5.123532 6.345311 8.453634 14.645454	8.675456 8.654542 8.543436 8.543557 8.324568	0.95
		3.675675 6.675798 8.754539 3.351231 9.435234	11.235457 7.235457 1.346543 2.347567 4.325798	0.92
		8.765769 2.653543 1.4354687 2.877476 6.543565	4.214235 3.2315342 1.243534 9.23523 8.231534	0.93

the outputs from the past and the present. Thanks to its memory, the network can learn long-term relationships in a sequence, which allows it to classify sentiments while considering the whole context, or predict the next word in a sentence.

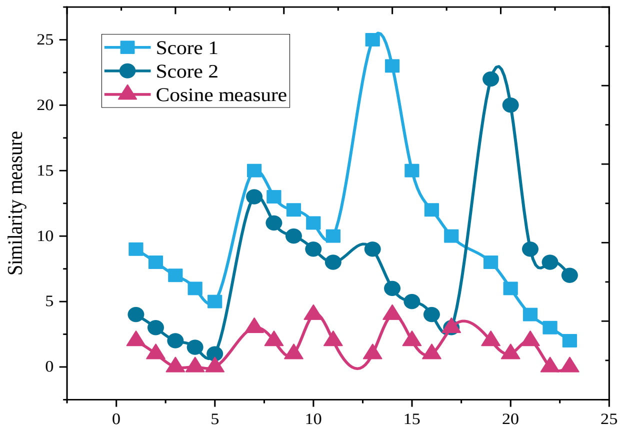


Figure 8. *Comparison of similarity measure*

3.14 Emoji Anticipation

Emoji To Text:

Our baseline text model is built upon a word embedding layer and a bidirectional LSTM that analyses the text in both regular order and reverse order [80]. Although LSTMs employ their memory to highlight pertinent information, information propagation is still degraded. In order to counteract this effect and guarantee that information from the beginning of the sentence is retained in the representation, the LSTM is bi-directional. Our bi-directional LSTM layers take words into a vector embedding space, combine the resulting representations, then feed the mixture to a softmax layer, which aims to predict appropriate emoji. The model is trained using tokenized text from the Twemoji dataset. To prevent overfitting, the validation set is utilised to calculate the number of epochs at which to end training.

Emoji to Image:

We can use our data to train a model for image-to-emoji prediction, which is similar to the method for text-based prediction. We depict the visuals that go along with tweets using a CNN. Thirteen thousand ImageNet classes can be predicted by this GoogLeNet architecture [81]. For our picture input, we employ the representation that was produced at the penultimate layer. On top of this representation, we train a single soft-max layer with the goal of emoji prediction, and we freeze the weights before this softmax. If there was enough training data, an end-to-end convolutional model could also be trained; however, gathering the necessary quantity of training samples would be challenging, especially for the longtail of the emoji usage distribution.

Combination:

We apply a late fusion strategy for the merging of both text and image modalities. The format of the text-based neural network and the image-based convolutional network is directly equivalent since they both provide emoji confidence ratings in a softmax layer. We provide a combination prediction given confidence scores pimg(yjximg) for some picture ximg and confidence scores ptxt(yjxtxt) predicting the likelihood of a given emoji y for some text xtxt. Figure 9 shows the ambiguous faces are difficult to predict, while emoji tied concretely to an event, object, or place tend to be the easiest.

Figure 9. *Examples of the hardest emoji to predict (red), the easiest (green), and those in between.*

Table 8. *Top emojis that correspond to each emotion category.*

Emotion	Most correlated Emojis						
Amusement	0.34	0.67	0.33	0.98	0.17	0.11	0.14
Anger	0.44	0.67	0.78	0.78	0.89	0.56	0.67
Awe	0.45	0.49	0.23	0.67	0.34	0.56	0.21
Contentment	0.34	0.18	0.18	0.19	0.13	0.71	0.23
Disgust	0.56	0.78	0.78	0.67	0.22	0.87	0.89
Excitement	0.23	0.34	0.12	0.18	0.10	0.34	0.45
Fear	0.12	0.11	0.22	0.67	0.16	0.67	0.78
Sadness	0.93	0.92	0.87	0.78	0.98	0.23	0.56

Emojis and Emotions

With our SmileyNet, all of the "5 agrees" split images are immediately incorporated into the emoji space. Figure 10 shows the top SmileyNet predictions for specific test photos taken from Twitter. Our approach produces precise forecasts that capture the overall tone of the picture. Our system offers sentiment emojis with different polarities when the input image has sub-images or when the primary sentiment region is out of focus. This may have anything to do with the overall SmileyNet plan. The theory is that region-based or attention-based processing could aid in identifying and prioritising the most crucial visual region for result prediction (table8). Finally, predictions might be useful for both traditional uses like sentiment analysis and novel ones like detecting violence.

Figure 10*. Top 5 emojis predicted per image with SmileyNet*

3.15 Emoji Use Factors Implementing User Preferences

Research now concentrates on describing consumers' emoji preferences without delving further into the underlying causes. Emoji like "heart" and "tears of joy" were discovered to be more popular; however, it is unknown if this is because of any particular cultural characteristic. Emoji preferences are shaped by a variety of aspects, all of which are worth investigating . These include familiarity with emoji, interpersonal interactions, contextual information, and personal interpretations of emoji beyond official definitions. The Effect of Stickers on Emoji Emoji's standing has been affected by the introduction and extensive use of stickers, and some research has started to enhance the stickers' user experience [82]. Researchers find it interesting to wonder if stickers may eventually take the role of emoji. Under the influence of stickers, it's also worthwhile to investigate ways to increase emoji's ability to convey emotion and meaning while also enhancing user experience [83].

The connection between the use of emojis and social development

the creation and application of emoji in popular culture is a reflection of particular political and cultural traits [84]. Numerous scholars have approached the social impact of emojis from various angles. For instance, some inappropriate emoji usage can lower public awareness, a fact that the general public has not yet come to understand [85]. According to some researchers, emoji's widespread use is a reflection of multicultural communication and cultural globalisation. The use of emoji and other non-verbal cues may have an unconscious influence that perpetuates social inequality and exploitation [86]. For instance, contends that the quantitative application of emoji in the workplace (e.g., using emoji to assign ratings) has reduced employee autonomy by treating them like an interchangeable part in a digital economy warehouse [87].

We should also talk about the democratisation of Unicode and emoji choices. In order to remedy the dearth of ethnic representation, emoji with various skin tones have been produced. Furthermore, emoji related to menstruation were recently authorised by the Unicode consortium, a sign that women's rights are growing and a step towards eliminating "menstrual shame [88]." Future studies might therefore examine the deeper significance of emoji use from other angles, particularly the connections between emoji use and social inequity, political movements, and subcultural groupings [89]

4. Conclusions

In order to give academics interested in emoji a global perspective and some direction, this publication systematically examines related research on emoji. This paper provides an overview of the emoji research domains, usage aspects, functional attributes, and development process. Emojis are emotive and semantic in nature, and they evolved from emoticons. Emoji usage is impacted by and varies depending on personal circumstances, culture, and social media platforms. Differing circumstances and cultural backgrounds might give rise to ambiguity and misinterpretation. This paper thoroughly examines the research topics, methodologies, and instruments employed in emoji studies from the perspectives of many fields (communication, computing, behavioural science, marketing, and education). It also systematically summarises the state of emoji research in these fields and offers some fresh ideas for future emoji research, including emotional association, use preference, new modalities, and societal impacts.

Two models are constructed to predict future emoji inputs from pictures. In the media, information regarding photographs is represented through both textual and emoji content. As a result, images may be used to accurately predict future emoji entries when compared to text. Thus, this model helps us by anticipating the next entry from images in the quickest amount of time and by optimising speed and performance. The three models that went into creating the Emoji Model are CNN, SmileyNet, and Word2Vec. Furthermore, we demonstrate that the interpretability of our embedding makes it suitable for sentiment analysis in a zero-shot learning setting without the need for further training. Finally, first results show that our embedding can facilitate new applications like violence and abuse detection that depend on extracting emotion from visual input. The results of this work should be of interest to the computer vision and visual sentiment analysis groups as well as the domains of social media research and emoji modality interpretation.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
- **Acknowledgement:** The authors declare that they have nobody or no-company to acknowledge.

  Author contributions: Prof.Dr.PC Lakshmi Narayanan and Prof.Dr. Kishore Kunal conceptualized the research problem, designed the methodology involving CNN architecture and emoji2vec embedding, and conducted the literature review on emojis in digital communication and sentiment embeddings. Dr.Vairavel Madeshwaren and Dr.Sudhakar Ganesan Implemented the CNN model for image classification, developed the sentiment analysis framework for emoji label prediction, and integrated the findings into the predictive model. Dr.Anitha Jaganathan and Dr.Vairavel Madeshwaren preprocessed datasets, fine-tuned model parameters, analyzed results, and generated visual representations to evaluate the comparative performance of the proposed methods.coordinated manuscript writing, supervised the research process, ensured technical accuracy, and reviewed the paper for journal compliance and quality.

  Acknowledgement

  I sincerely thank my co-author for their valuable insights and contributions to this research. I also appreciate the support from colleagues who provided constructive feedback. Lastly, I acknowledge the resources that facilitated the successful completion of this work.
- **Funding information:** The authors declare that there is no funding to be acknowledged.

- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

References

[1] Al-Halah, Z., Aitken, A., Shi, W., & Caballero, J. (2019). Smile, be happy :) emoji embedding for visual sentiment analysis. *Proceedings of the IEEE/CVF International Conference on Computer Vision Workshops*, 0–0.

[2] Alam, S., & Yao, N. (2019). The impact of preprocessing steps on the accuracy of machine learning algorithms in sentiment analysis. *Computational and Mathematical Organization Theory, 25*(9), 319–335. https://doi.org/10.1007/s10588-018-9266-8

[3] Arulmurugan, R., Sabarmathi, K. R., & Anandakumar, H. (2019). **[Retracted article]** Classification of sentence-level sentiment analysis using cloud machine learning techniques. *Cluster Computing, 22*(1), 1199–1209. https://doi.org/10.1007/s10586-022-03861-3

[4] Baek, T. H., Kim, S., Yoon, S., Choi, Y. K., Choi, D., & Bang, H. (2022). Emojis and assertive environmental messages in social media campaigns. *Internet Research, 32*(3), 988–1002. https://doi.org/10.1108/INTR-11-2020-0638

[5] Bai, Q., Dan, Q., Mu, Z., & Yang, M. (2019). A systematic review of emoji: Current research and future perspectives. *Frontiers in Psychology, 10*, 2221. https://doi.org/10.3389/fpsyg.2019.02221

[6] Bansal, B., & Srivastava, S. (2019). Lexicon-based Twitter sentiment analysis for vote share prediction using emoji and N-gram features. *International Journal of Web Based Communities, 15*(1), 85–99. https://doi.org/10.1504/IJWBC.2019.098693

[7] Barbieri, F., Ballesteros, M., Ronzano, F., & Saggion, H. (2018). Multimodal emoji prediction. *arXiv Preprint*. https://doi.org/10.48550/arXiv.1803.02392

[8] Beaufays, F., Rao, K., Mathews, R., & Ramaswamy, S. (2019). Federated learning for emoji prediction in a mobile keyboard.

[9] Beißwenger, M., & Pappert, S. (2019). How to be polite with emojis: A pragmatic analysis of face work strategies in an online learning environment. *European Journal of Applied Linguistics, 7*(2), 225–254. https://doi.org/10.1515/eujal-2019-0003

[10] Cappallo, S., Mensink, T., & Snoek, C. G. (2015). Image2emoji: Zero-shot emoji prediction for visual media. *Proceedings of the 23rd ACM International Conference on Multimedia, 8*, 1311–1314. https://doi.org/10.1145/2733373.2806335

[11] Cappallo, S., Svetlichnaya, S., Garrigues, P., Mensink, T., & Snoek, C. G. (2018). New modality: Emoji challenges in prediction, anticipation, and retrieval. *IEEE Transactions on Multimedia, 21*(2), 402–415. https://doi.org/10.1109/TMM.2018.2862363

[12] Chatterjee, A., Gupta, U., Chinnakotla, M. K., Srikanth, R., Galley, M., & Agrawal, P. (2019a). Understanding emotions in text using deep learning and big data. *Computers in Human Behavior, 93*(4), 309–317. https://doi.org/10.1016/j.chb.2018.12.029

[13] Chatterjee, A., Narahari, K. N., Joshi, M., & Agrawal, P. (2019b). SemEval-2019 task 3: EmoContext contextual emotion detection in text. *Proceedings of the 13th International Workshop on Semantic Evaluation, 6*, 39–48. https://doi.org/10.18653/v1/S19-2005

[14] Chen, Z., Cao, Y., Lu, X., Mei, Q., & Liu, X. (2019a). Sentimoji: An emoji-powered learning approach for sentiment analysis in software engineering. *Proceedings of the 2019 27th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering, 8*, 841–852. https://doi.org/10.1145/3338906.3338977

[15] Chen, Z., Shen, S., Hu, Z., Lu, X., Mei, Q., & Liu, X. (2019b). Emoji-powered representation learning for cross-lingual sentiment classification. *The World Wide Web Conference, 6*, 251–262. https://doi.org/10.1145/3308558.3313600

[16] Choudhary, N., Singh, R., Rao, V. A., & Shrivastava, M. (2018). Twitter corpus of resource-scarce languages for sentiment analysis and multilingual emoji prediction. *Proceedings of the 27th International Conference on Computational Linguistics*, 8, 1570–1577. https://aclanthology.org/C18-1133

[17] Coman, A. C., Zara, G., Nechaev, Y., Barlacchi, G., & Moschitti, A. (2018). Exploiting deep neural networks for tweet-based emoji prediction. *International Workshop on Semantic Evaluation*, 4(1).

[18] Felbo, B., Mislove, A., Søgaard, A., Rahwan, I., & Lehmann, S. (2017). Using millions of emoji occurrences to learn any-domain representations for detecting sentiment, emotion, and sarcasm. *arXiv Preprint*, arXiv:1708.00524. https://doi.org/10.48550/arXiv.1708.00524

[19] Field, E. (2021). Is it all just emojis and LOL: Or can social media foster environmental learning and activism? *Education for Democracy 2.0: Changing Frames of Media Literacy*, 6(1), 198. https://doi.org/10.1163/9789004448490_012

[20] Fuhl, W., Bozkir, E., Hosp, B., Castner, N., Geisler, D., Santini, T. C., & Kasneci, E. (2019). Encodji: Encoding gaze data into emoji space for an amusing scanpath classification approach. *Proceedings of the 11th ACM Symposium on Eye Tracking Research & Applications*, 6, 1–4. https://doi.org/10.1145/3314111.3323074

[21] Garain, A. (2019). Humor analysis based on human annotation (HAHA)-2019: Humor analysis at tweet level using deep learning. *IberLEF@SEPLN*, 191–196.

[22] Gertner, A. S., Henderson, J., Merkhofer, E., Marsh, A., Wellner, B., & Zarrella, G. (2019). MITRE at SemEval-2019 Task 5: Transfer learning for multilingual hate speech detection. *Proceedings*

of the 13th International Workshop on Semantic Evaluation, 6, 453–459. http://dx.doi.org/10.18653/v1/S19-2080
[23] Ghaban, W. (2022). Do we speak the same language? The effect of emojis on learners in an online learning environment. *International Conference on Human-Computer Interaction*, 6, 414–426.
[24] Golazizian, P., Sabeti, B., Asli, S. A. A., Majdabadi, Z., Momenzadeh, O., & Fahmi, R. (2020). Irony detection in Persian language: A transfer learning approach using emoji prediction. *Proceedings of the Twelfth Language Resources and Evaluation Conference*, 5, 2839–2845. https://aclanthology.org/2020.lrec-1.346
[25] Guibon, G., Ochs, M., & Bellot, P. (2018). From emoji usage to categorical emoji prediction. In *International Conference on Computational Linguistics and Intelligent Text Processing* (Vol. 13397, pp. 329–338). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-23804-8_26
[26] Gupta, A., Bhatia, B., Chugh, D., Himabindu, G. S., Sethia, D., Agarwal, E., Sani, D., & Garg, S. (2021). Context-aware emoji prediction using deep learning. In *International Conference on Artificial Intelligence and Speech Technology*, 11, 244–254. https://doi.org/10.1007/978-3-030-95711-7_22
[27] Himabindu, G. S. N., Rao, R., & Sethia, D. (2022). A self-attention hybrid emoji prediction model for code-mixed language (Hinglish). *Social Network Analysis and Mining*, 12(1), 137. https://doi.org/10.1007/s13278-022-00961-1
[28] Ibrohim, M. O., Setiadi, M. A., & Budi, I. (2019). Identification of hate speech and abusive language on Indonesian Twitter using Word2vec, part of speech, and emoji features. *Proceedings of the 1st International Conference on Advanced Information Science and System*, 11, 1–5. https://doi.org/10.1145/3373477.3373495
[29] Illendula, A., & Sheth, A. (2019). Multimodal emotion classification. *Companion Proceedings of the 2019 World Wide Web Conference*, 5, 439–449. https://doi.org/10.1145/3308560.3316549
[30] Inan, E. (2020). An active learning-based emoji prediction method in Turkish. *International Journal of Intelligent Systems and Applications in Engineering*, 8(1), 1–5. https://doi.org/10.18201/ijisae.2020158882
[31] Jabreel, M., & Moreno, A. (2019). A deep learning-based approach for multi-label emotion classification in tweets. *Applied Sciences*, 9(6), 1123. https://doi.org/10.3390/app9061123
[32] Jain, A., & Jain, V. (2019). Sentiment classification of Twitter data belonging to renewable energy using machine learning. *Journal of Information and Optimization Sciences*, 40(2), 521–533. https://doi.org/10.1080/02522667.2019.1582873
[33] Jaques, N., Ghandeharioun, A., Shen, J. H., Ferguson, C., Lapedriza, A., Jones, N., & Picard, R. (2019). Way off-policy batch deep reinforcement learning of implicit human preferences in dialog. *arXiv Preprint*, arXiv:1907.00456. https://doi.org/10.48550/arXiv.1907.00456
[34] Jiang, H., Guo, A., & Ma, J. (2020). Automatic prediction and insertion of multiple emojis in social media text. In *2020 International Conferences on Internet of Things (iThings), IEEE Green Computing and Communications (GreenCom), IEEE Cyber, Physical and Social Computing (CPSCom), IEEE Smart Data (SmartData), and IEEE Congress on Cybermatics (Cybermatics)* (Vol. 11, pp. 505–512). IEEE.
[35] Jin, S., & Pedersen, T. (2018). Duluth UROP at SemEval-2018 Task 2: Multilingual emoji prediction with ensemble learning and oversampling. *arXiv Preprint*, arXiv:1805.10267. https://doi.org/10.48550/arXiv.1805.10267
[37] Kapočiūtė-Dzikienė, J., Damaševičius, R., & Woźniak, M. (2019). Sentiment analysis of Lithuanian texts using traditional and deep learning approaches. *Computers, 8*(1), 4. https://doi.org/10.3390/computers8010004
[38] Kim, J., Gong, T., Kim, B., Park, J., Kim, W., Huang, E., Han, K., Kim, J., Ko, J., & Lee, S. J. (2020). No more one-liners: Bringing context into emoji recommendations. *ACM Transactions on Social Computing, 3*(2), 1–25. https://doi.org/10.1145/3373146
[39] Kim, Y., & Jun, J. W. (2020). Factors affecting sustainable purchase intentions of SNS emojis: Modeling the impact of self-presentation. *Sustainability, 12*(20), 8361. https://doi.org/10.3390/su12208361
[40] Koch, T. K., Romero, P., & Stachl, C. (2022). Age and gender in language, emoji, and emoticon usage in instant messages. *Computers in Human Behavior, 126*, 106990. https://doi.org/10.1016/j.chb.2021.106990
[41] Kolla, V., & Kiran, R. (2021). Emojify: A deep learning approach for custom emoji creation and recognition. *International Journal of Creative Research Thoughts, 9*(1), 4859–4866. https://ssrn.com/abstract=4413719
[42] Kollipara, V. D. P., Kollipara, V. H., & Prakash, M. D. (2021). Emoji prediction from Twitter data using a deep learning approach. *Asian Conference on Innovation in Technology (ASIANCON), 8*, 1–6. https://doi.org/10.1109/ASIANCON51346.2021.9544680
[43] Kumar, A., & Garg, G. (2023). Empirical study of shallow and deep learning models for sarcasm detection using context in benchmark datasets. *Journal of Ambient Intelligence and Humanized Computing, 14*(5), 5327–5342. https://doi.org/10.1007/s12652-019-01419-7
[44] Kunte, A. V., & Panicker, S. (2019). Using textual data for personality prediction: A machine learning approach. *2019 4th International Conference on Information Systems and Computer Networks (ISCON), 11*, 529–533. https://doi.org/10.1109/ISCON47742.2019.9036220
[45] Lavanya, K., Devi, C. L., Sree, M. D., & Shareef, P. N. (2021). Predicting emotions based on emojis and speech using machine learning techniques.

International Journal of Creative Research Thoughts, 8(6), 552–557.

[46] Lee, S., Jeong, D., & Park, E. (2022). MultiEmo: Multi-task framework for emoji prediction. *Knowledge-Based Systems, 242*, 108437. https://doi.org/10.1016/j.knosys.2022.108437

[47] Li, D., Rzepka, R., Ptaszynski, M., & Araki, K. (2019). A novel machine learning-based sentiment analysis method for Chinese social media considering Chinese slang lexicon and emoticons. *AffCon@AAAI, 1*, 2328.

[48] Li, D., Rzepka, R., Ptaszynski, M., & Araki, K. (2020). HEMOS: A novel deep learning-based fine-grained humor detecting method for sentiment analysis of social media. *Information Processing & Management*, *57*(6), 102290. https://doi.org/10.1016/j.ipm.2020.102290

[49] Li, W., Chen, Y., Hu, T., & Luo, J. (2018). Mining the relationship between emoji usage patterns and personality. *Proceedings of the International AAAI Conference on Web and Social Media, 12*(1), 648–651. https://doi.org/10.1609/icwsm.v12i1.15054

[50] Li, X., Zhang, J., Du, Y., Zhu, J., Fan, Y., & Chen, X. (2023). A novel deep learning-based sentiment analysis method enhanced with emojis in microblog social networks. *Enterprise Information Systems, 17*(5), 2037160. https://doi.org/10.1080/17517575.2022.2037160

[51] Liebeskind, C., & Liebeskind, S. (2019). Emoji prediction for Hebrew political domain. *Companion Proceedings of the 2019 World Wide Web Conference, 5*, 468–477. https://doi.org/10.1145/3308560.3316548

[52] Liu, L., Priestley, J. L., Zhou, Y., Ray, H. E., & Han, M. (2019). A2text-net: A novel deep neural network for sarcasm detection. *2019 IEEE First International Conference on Cognitive Machine Intelligence (CogMI), 12*, 118–126. https://doi.org/10.1109/CogMI48466.2019.00025

[53] López-Santamaría, L. M., Gomez, J. C., Almanza-Ojeda, D. L., & Ibarra-Manzano, M. A. (2019). Age and gender identification in unbalanced social media. *2019 International Conference on Electronics, Communications and Computers (CONIELECOMP), 12*, 74–80. https://doi.org/10.1109/CONIELECOMP.2019.8673125

[54] Ma, W., Liu, R., Wang, L., et al. (2020). Emoji prediction: Extensions and benchmarking. *arXiv preprint arXiv:2007.07389.* https://doi.org/10.48550/arXiv.2007.07389

[55] Meenigea, N. (2019). Emojify—Create your own emojis with deep learning. *International Journal of Sustainable Development in Computing Science, 1*(1), 31–39.

[56] Nerellapalli, V. (2019). Sentimental analysis—Emoji prediction. *International Journal of Emerging Technologies and Innovation Research Literature.*

[57] Peng, D., & Zhao, H. (2021). Seq2Emoji: A hybrid sequence generation model for short text emoji prediction. *Knowledge-Based Systems, 214*, 106727. https://doi.org/10.1016/j.knosys.2020.106727

[58] Peng, S., Cao, L., Zhou, Y., Ouyang, Z., Yang, A., Li, X., & Yu, S. (2022). A survey on deep learning for textual emotion analysis in social networks. *Digital Communications and Networks, 8*(5), 745–762. https://doi.org/10.1016/j.dcan.2021.10.003

[59] Pinto, J., Priya, V., & Murari. (2019). Real-time sentiment analysis of political Twitter data using a machine learning approach. *International Research Journal of Engineering and Technology (IRJET), 6*(4), 4124–4129.

[60] Priya, B., & Gnana. (2019). Emoji-based sentiment analysis using KNN. *International Journal of Scientific Research and Review, 7*(4), 859–865.

[61] Raj, H., Wilfred, S., & Balachandran. (2020). Future emoji entry prediction using neural networks. *Journal of Computer Science, 16*(2), 150–157. https://doi.org/10.3844/jcssp.2020.150.157

[62] Ramaswamy, S., Mathews, R., Rao, K., & Beaufays, F. (2019). Federated learning for emoji prediction in a mobile keyboard. *arXiv preprint arXiv:1906.04329.* https://doi.org/10.48550/arXiv.1906.04329

[63] Ranjan, R., & Yadav, P. (2021). Emoji prediction using LSTM and Naive Bayes. *TENCON 2021-2021 IEEE Region 10 Conference (TENCON), 12*, 284–288. https://doi.org/10.1109/TENCON54134.2021.9707344

[64] Rebiai, Z., Andersen, S., Debrenne, A., & Lafargue, V. (2019). SCIA at SemEval-2019 task 3: Sentiment analysis in textual conversations using deep learning. *Proceedings of the 13th International Workshop on Semantic Evaluation, 6*, 297–301. https://doi.org/10.18653/v1/S19-2051

[65] Ronzano, F., Barbieri, F., Wahyu Pamungkas, E., Patti, V., & Chiusaroli, F. (2018). Overview of the Evalita 2018 Italian emoji prediction (ITAMoji) task. *CEUR Workshop Proceedings, 2263*, 1–9. http://ceur-ws.org/Vol-2263/paper004.pdf

[66] Saha, S., & Kumar, K. A. (2022). Emoji prediction using emerging machine learning classifiers for text-based communication. *Journal of Mathematical Sciences & Computing, 1*, 37–43. https://doi.org/10.5815/ijmsc.2022.01.04

[67] Santamaría-Bonfil, G., & López, O. G. T. (2019). Emoji as a proxy of emotional communication. *Becoming Human with Humanoid—From Physical Interaction to Social Intelligence*. IntechOpen. https://doi.org/10.5772/intechopen.73377

[68] Shardlow, M., Gerber, L., & Nawaz, R. (2022). One emoji, many meanings: A corpus for the prediction and disambiguation of emoji sense. *Expert Systems with Applications, 198*(7), 116862. https://doi.org/10.1016/j.eswa.2022.116862

[69] Subramanian, J., Sridharan, V., Shu, K., & Liu, H. (2019). Exploiting emojis for sarcasm detection. *Social, Cultural, and Behavioral Modeling: 12th International Conference,* 70–80. Springer International Publishing.

[70] Tavan, E., Rahmati, A., & Keyvanrad, M. A. (2020). Persian emoji prediction using deep learning and emoji embedding. *2020 10th International Conference on Computer and Knowledge Engineering (ICCKE), 10*, 350–355. https://doi.org/10.1109/ICCKE50421.2020.9303639

[71] Tomihira, T., Otsuka, A., Yamashita, A., & Satoh, T. (2018). What does your tweet emotion mean? Neural emoji prediction for sentiment analysis. *Proceedings of the 20th International Conference on Information Integration and Web-Based Applications & Services*, *11*, 289–296. https://doi.org/10.1145/3282373.3282406

[72] Tomihira, T., Otsuka, A., Yamashita, A., & Satoh, T. (2020a). Multilingual emoji prediction using BERT for sentiment analysis. *International Journal of Web Information Systems, 16*(3), 265–280. https://doi.org/10.1108/IJWIS-09-2019-0042

[73] Tomihira, T., Otsuka, A., Yamashita, A., & Satoh, T. (2020b). Multilingual emoji prediction using BERT for sentiment analysis. *International Journal of Web Information Systems, 16*(3), 265–280. https://doi.org/10.1108/IJWIS-09-2019-0042

[74] Venkit, P., Karishma, Z., Hsu, C. Y., Katiki, R., Huang, K., Wilson, S., & Dudas, P. (2021). A 'Sourceful' twist: Emoji prediction based on sentiment, hashtags and application source. *arXiv preprint arXiv:2103.07833.* https://doi.org/10.48550/arXiv.2103.07833

[75] Wijeratne, S., Saggion, H., Kiciman, E., & Sheth, A. P. (2020). Emoji understanding and applications in social media: Lay of the land and special issue introduction. *ACM Transactions on Social Computing,* *3*(2), 1–5. https://doi.org/10.1145/3386120

[76] Winata, G. I., Madotto, A., Lin, Z., Shin, J., Xu, Y., Xu, P., & Fung, P. (2019). CAiRE HKUST at SemEval-2019 task 3: Hierarchical attention for dialogue emotion classification. *arXiv preprint arXiv:1906.04041*. https://doi.org/10.48550/arXiv.1906.04041

[77] Xiao, J. (2019). Figure eight at SemEval-2019 task 3: Ensemble of transfer learning methods for contextual emotion detection. *Proceedings of the 13th International Workshop on Semantic Evaluation,* *6*, 220–224. https://doi.org/10.18653/v1/S19-2036

[78] Xing, W., & Du, D. (2019). Dropout prediction in MOOCs: Using deep learning for personalized intervention. *Journal of Educational Computing Research,* *57*(3), 547–570. https://doi.org/10.1177/0735633118757015

[79] Xu, M., Liu, J., Liu, Y., Lin, F. X., Liu, Y., & Liu, X. (2019). A first look at deep learning apps on smartphones. *The World Wide Web Conference, 6,* 2125–2136. https://doi.org/10.1145/3308558.3313591

[80] Zhang, L., Zhou, Y., Erekhinskaya, T., & Moldovan, D. (2020). Emoji prediction: A transfer learning approach. *Advances in Information and Communication: Proceedings of the 2020 Future of Information and Communication Conference (FICC), 2*, 864–872. https://doi.org/10.1007/978-3-030-39442-4_65

[81] Zhao, L., & Zeng, C. (2017). Using neural networks to predict emoji usage from Twitter data. *Semantic Scholar*, 1–6.

[82] Zhao, P., Jia, J., An, Y., Liang, J., Xie, L., & Luo, J. (2018). Analyzing and predicting emoji usages in social media. *Companion Proceedings of the The Web Conference,* *4*, 327–334. https://doi.org/10.1145/3184558.3186344

[83] Zhu, J., Tian, Z., & Kübler, S. (2019). UM-IU@LING at SemEval-2019 task 6: Identifying offensive tweets using BERT and SVMs. *arXiv preprint arXiv:1904.03450.* https://doi.org/10.48550/arXiv.1904.03450

[84] Pradeepa, K., Bharathiraja, N., Meenakshi, D., Hariharan, S., Kathiravan, M., & Kumar, V. (2022). Artificial neural networks in healthcare for augmented reality. In 2022 Fourth International Conference on Cognitive Computing and Information Processing (CCIP), 1–5. https://doi.org/10.1109/CCIP57447.2022.10058670

[85] Kathiravan, M., Ramya, M., Jayanthi, S., Reddy, V. V., Ponguru, L., & Bharathiraja, N. (2023). Predicting the sale price of pre-owned vehicles with the ensemble ML model. In 2023 4th International Conference on Electronics and Sustainable Communication Systems (ICESC), 1793–1797. https://doi.org/10.1109/ICESC57686.2023.10192988

[86] Bhaskaran, S., Hariharan, S., Veeramanickam, M. R., Bharathiraja, N., Pradeepa, K., & Marappan, R. (2022). Recommendation system using inference-based graph learning–modeling and analysis. In 2022 2nd International Conference on Innovative Sustainable Computational Technologies (CISCT), 1–5. https://doi.org/10.1109/CISCT55310.2022.10046447

[87] Anand, M., Antonidoss, A., Balamanigandan, R., Rahmath Nisha, S., Gurunathan, K., & Bharathiraja, N. (2022). Resourceful routing algorithm for mobile ad-hoc network to enhance energy utilization. Wireless Personal Communications, 127(Suppl 1), 7–8. https://doi.org/10.1007/s11277-021-08570-5

[88] Menaka, S., Harshika, J., Philip, S., John, R., Bharathiraja, N., & Murugesan, S. (2023). Analysing the accuracy of detecting phishing websites using ensemble methods in machine learning. In 2023 Third International Conference on Artificial Intelligence and Smart Energy (ICAIS), 1251–1256. https://doi.org/10.1109/ICAIS56108.2023.10073834

[89] Shyni Carmel Mary, S., Kishore Kunal, & Madeshwaren, V. (2025). IoT and Blockchain in Supply Chain Management for Advancing Sustainability and Operational Optimization. International Journal of Computational and Experimental Science and Engineering, 11(1). https://doi.org/10.22399/ijcesen.1103