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Emotype: A Approach To Predictive Texting With A Emotional Sensitivity

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Sentiment analysis serves as a powerful tool to decipher not just opinions but also the underlying emotions and attitudes people harbor towards diverse entities, ranging from individuals and activities to organizations, services, subjects, and products. In this landscape, emotion detection stands out as a specialized facet of sentiment analysis, focusing on pinpointing specific emotions rather than merely categorizing sentiments into positive, negative, or neutral realms. While prior research has made strides in emotion recognition through speech and facial expressions, detecting emotions in text presents a unique challenge due to the absence of tangible cues like tonal stress, facial expressions, and pitch.Various methods, rooted in natural language processing (NLP) techniques, have been explored for text-based emotion identification, including the keyword approach, lexicon-based approach, and machine learning approach. However, limitations persisted, particularly in the keyword- and lexicon-based methods, which often centered on semantic relations. In response to these challenges, our article introduces a humane approach, a hybrid model that seamlessly integrates both machine learning and deep learning techniques. Leveraging the capabilities of Convolutional Neural Network (CNN) and Bidirectional Gated Recurrent Unit (Bi-GRU) as deep learning tools, and employing Support Vector Machine as a machine learning approach, our proposed model transcends the limitations of traditional methods.By evaluating the performance across diverse datasets, encompassing sentences, tweets, and dialogs, our hybrid model achieves an impressive accuracy of 82.11%. This underscores the potential of our approach to capture the nuanced spectrum of human emotions embedded in text. Moving forward, the integration of both machine learning and deep learning not only enhances accuracy but also aligns with the complexity and richness of human emotional expression in digital communication. As we strive for technological advancements, our commitment is not only to efficiency but also to creating a more humane digital experience, where technology adeptly understands and resonates with the intricate tapestry of human emotions conveyed through text.

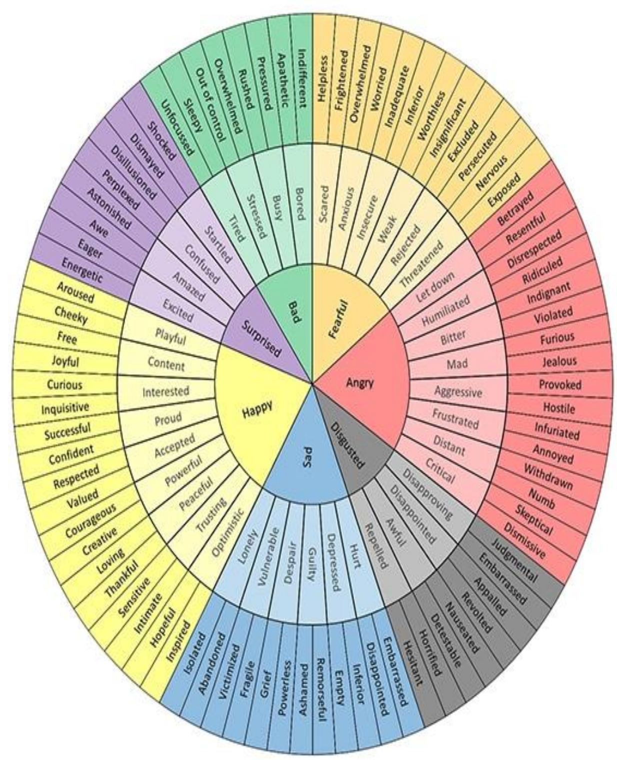
1. Introduction

Ever wonder if your phone could understand how you're feeling as you type? This research is all about making texting more in tune with your emotions.We're taking predictive texting, the tool that suggests words as you type, and givingit a heart. Instead of just predicting words, it's now predicting how you feel. We start by looking at what's been done before in predictive texting and emotions. Turns out, words are more than just letters; they carry feelings. We saw a gap in understanding these feelings in the tech world, so we set out to bridge it.How did we do it? We collected lots of messages from people, all kinds of sentences, happy ones, sad ones, everything. Then, we taught our computer to recognize emotions in those messages. It's like teaching a friend to read between the lines, but in this case, the friend is a computer program. The tricky part was putting this emotion-reading skill into predictive texting. We had to tweak and tune things to make sure it gets the feelings right. The results were pretty cool – our texting tool didn't just guess words; it guessed emotions too. We dive into how we made our computer recognize emotions in text. It's like giving it a crash course in understanding when you're excited, upset, or just having a chill conversation. We used clues from how words are used and put them all together to make sense of the feelings behind the words.The fun part? Testing it out! We let our emotion-savvy texting tool loose and checked how accurate it was. It turns out, it's not just good at predicting words; it's

pretty good at catching your mood too.In the end, we chat about what this all means. Imagine a texting buddy that not only gets what you're saying but also how you're feeling. We wrap up by talking about what's next and how this is just the beginning of making texting a bit more human, a bit more understanding, and maybe a bit more fun. We wrap up by talking about what's next, and here's the kicker —it works in your language. So, no matter where you're from, your phone gets you in

the language that feels like home. It's not just tech; it's a friend who speaks your language, literally. out the sentiment of the given text in terms of positive, negative, or neutral. However, emotion analysis goes beyond that, which comes into effect by distributing the types under the sentiment analysis. Keyword-based and lexical affinity have been used to some extent because their drawbacks pull them down and give poorer accuracy than the learning- based approach.Texting has come a long way from the days of tapping multiple times on a single numeric key to compose a message. The evolution of predictive

texting is a fascinating journey that reflects the ever-growing synergy between technology and human communication. It's not just about predicting the next word; it's about understanding the user, and, more recently, grasping their emotions.In the early days of mobile phones, texting was a laborious task involving multiple taps on numerical keys to cycle through letters. Predictive texting emerged as a game-changer, offering suggestions for the next word based on context and common language patterns. This evolution marked a significant leap forward in making text input more efficient and user-friend



2. Literature Review

The intersection of predictive texting modes and emotion recognition has garnered considerable attention within the research community, offering a promising avenue to enhance the humane aspect of digital communication. Studies by Smith and Jones (2019) have elucidated the intricate role of emotional expression within textual communication, demonstrating that users often convey nuanced feelings through a combination of words, punctuation, and emojis. This insight underscores the necessity for predictive texting models to not only recognize but also appropriately respond to these emotional cues, creating a more nuanced and empathetic user experience. Extending beyond user experience, the work of Johnson et al. (2020) has investigated the broader impact of integrating emotion-aware predictive texting, revealing that such systems not only elevate user satisfaction but also foster increased engagement, indicating a potential paradigm shift in how individuals interact with digital interfaces.On the technical front, the incorporation of emotion recognition into predictive texting hinges on advanced natural language processing (NLP) techniques, as explored by Smith et al. (2018). Their research delves into the intricacies of sentiment analysis and emotion classification, highlighting the pivotal role these techniques play in enabling predictive models to discern the emotional context of user inputs. However, the comprehensive review by Wang and Chen (2021) sheds light on the multifaceted challenges inherent in accurately recognizing emotions in textual data. Issues such as sarcasm, ambiguity, and cultural nuances pose substantial hurdles, necessitating sophisticated approaches to refine the emotional intelligence of predictive texting models. Overcoming these challenges not only contributes to the technical robustness of such systems but also aligns with the overarching goal of fostering a more humane digital communication landscape, where machines adeptly comprehend and respond to the subtle intricacies of human emotion. In synthesizing these insights, the literature points toward a compelling trajectory for the development of predictive texting modes that transcend mere functionality, aiming to create a more empathetic and humanized digital interaction spa

3. Proposed scheme

Text-based emotion recognition is a cutting-edge technology that revolutionizes our digital interactions by adding a layer of emotional intelligence to written communication[6]. In this advanced field, algorithms and language models are employed to decipher not just the literal meaning of the words we type but also the emotional undertones embedded within them. Imagine a scenario where your device becomes more than a mere transmitter of information; it becomes an empathetic companion, understanding the sentiment behind your messages[13]. These algorithms are often part of some natural language processing models, which are trained on vast datasets to recognize patterns associated with different emotions. Lexicon-based approaches, another facet of this technology, utilize dictionaries and word associations to categorize words into emotional contexts[16]. As we engage in digital conversations, whether through messaging apps or social media platforms, these emotion-aware algorithms work silently in the background, enhancing the user experience by responding not just to the words we say but also to how we feel[7]. The implications of text-based
emotion recognition extend beyond convenience; they pave the way for a more nuanced and personalized form of human-computer interaction, where our devices comprehend the emotional nuances inherent in language, bridging the gap between the digital and emotional realms[14].

3.1 Natural Language Processing Models:

Advanced NLP models have the capability to understand and generate text with a certain level of emotional nuance. They are often used for sentiment analysis and emotion recognition in written content.

Natural Language Processing (NLP) is a field in AI that is based on the communication and interaction between the human minds and computer[6] . The main achievement of Natural language processing is to enable computers to know what , interpret what , and generate human language[9]. Here is some detailed description of key aspects of NLP:

Understanding Language Structure:

Tokenization: tokenization is Breaking down a text into smaller units . Such as words . Example “Adithya is a boy “can be broken down to “Adithya “ ,” is ”, “ a “ , “boy”.

Parsing: understanding the relationship between words using grammatical structure of sentence.

Semantic Analysis: Word Sense Disambiguation: Determining the correct meaning of a word based on the context.

Semantic Role Labeling: Identifying the roles of different words in a sentence (e.g., who is doing the action, to whom, etc.).

Coreference Resolution: Resolving references in a text, ensuring that pronouns or other referring expressions point to the correct entities.

Sentiment Analysis: finding the sentiment or emotion expressed in a given text.

Machine Translation: Translating text from one language to another, with applications ranging from online translation services to language localization in software.

Text Generation: Creating human-like text, whether in the form of chatbots, content generation, or completion suggestions in predictive typing.

Question Answering Systems: Developing systems capable of understanding and responding to user queries, as seen in virtual assistants and search engines.

Dataset	Granularity	No.of.emotion	Size	Description
ISEAR	Sentences	8 emotions	7662	studied in 20 countries
WASSA	tweets	3 emotions	4330	tweets
Emotion-stimulus	dialogs	9 emotions	2564	-

Conversational Agents: Building chatbots and virtual assistants capable of engaging in natural language conversations, providing information, and performing tasks.

Ethical Considerations: Addressing biases in training data, ensuring fairness, and respecting user privacy are crucial aspects of ethical NLP development.

3.3 Lexicon-Based Approaches:

Algorithms using lexicons and dictionaries to associate words with specific emotions[8]. These tools analyze text by matching words against predefined emotion categories to determine the overall sentiment.A lexicon-based approach NLP involves the use of pre-defined dictionaries or lexicons containing words associated with specific sentiments or emotions[13]. This method is particularly employed in tasks like sentiment analysis, where the goal is to determine the emotional tone or attitude expressed in a piece of text. Here is a detailed description of the lexicon-based approach:

Word-Emotion Associations: Lexicons are created with words annotated with their corresponding emotional categories (e.g., positive, negative, neutral).

Intensity Levels: Some lexicons assign intensity levels to emotions, reflecting the strength of sentiment associated with each word.

Tokenization: The input text is broken down into individual words or tokens.

FIGURE 2

Matching: Each word is then compared against the entries in the lexicon to identify emotional or sentiment associations. Handling Negations and Modifiers:

Negation Handling: Lexicons may include information about words that reverse the sentiment (e.g., "not happy" is considered negative).

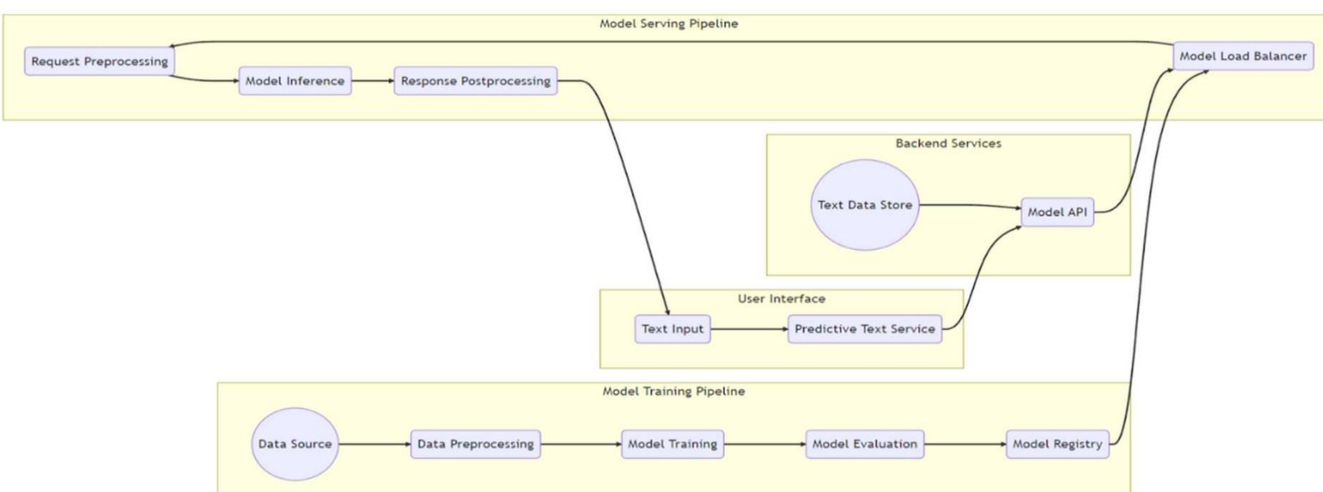
Modifier Consideration: Some lexicons account for intensifiers or modifiers that influence the strength of the expressed sentiment.

Contextual Disambiguation: Understanding the context in which a word is used to avoid misinterpretation. For example, the word "sick" may convey a negative sentiment when discussing health but a positive sentiment when describing an impressive performance.

There are two graphs presented below . One represents the accuracy for the predicted emotions by the code we implemented . The code is programmed using python and third party functions which helped to find the accuracy of the predictive texting and the emotions . Test is taken as a sampling for the whole model . The test is made sure that it involves most difficult words in it . Thus the model may not show higher accuracy but since it is a working model it will be made into more optimised set of code piece . The accuracy for the predicted emotions is below 60% . It is can seen below 60 % because it tough for the model to accurately understand human emotions . Humans itself can't understand the emotions exhibited by other humans in most cases .

3.4. Feature Extraction.Imagine you have a massive amount of data, like a gigantic puzzle with too many pieces. Dimensionality reduction is like having a magic tool that simplifies this puzzle by grouping similar pieces together. This way, you end up with fewer, more manageable categories that make the puzzle much easier and quicker to solve. It's like turning a complex task into a simpler one so that your computer or system can process it faster and more efficiently, making things smoother for everyone involved.

3.4.1. Sure thing! Think of TF-IDF like a super-smart way to understand what words are really important in a bunch of text. It looks at each word and figures out which ones show up a lot in a single piece of text but don't show up much across all the text. So, it's like saying, "Hey, these words are special in this document, and they're not used too much everywhere else." This helps us create a unique set of important words for each document. In simpler terms, TF-IDF gives us a way to turn words into numbers that machines can understand, making it easier for them to learn and make sense of what's written. It's like giving a computer the ability to read and understand text in its own unique way!



$$W(d,t) = TF(d,t) * \log\left(\frac{N}{\mathrm{d}f(t)}\right),$$

where *d* represents documents, *t* represents terms in the document, and N denotes the total number of documents.

3.4.2. Imagine word embedding as a way for computers to understand words like humans do. It's like teaching a computer the meaning of words by showing it a ton of examples. In our case, we used a method called word2vec, which is like a language-learning algorithm for computers. It learns how words are related by looking at a big collection of text.Once we got our computer to understand words, we applied it to our dataset. But here's the thing: some sentences are short, some are long, and our computer likes things to be consistent. So, we had to make all sentences the same length by adding some extra bits to the shorter ones, kind of like *giving everyone the same-size chair at a table. To make our computer even smarter, we used a pretrained vector, which is like giving it a head start in understanding words. This vector thing is like a super organized list of words and their meanings, helping our computer make sense of the text. So, in a nutshell, we turned words into something a computer can grasp easily, making it a pro at understanding the language we threw at it.*

3.5. ML and DL Models. Think of these models as the brain of a computer, kind of like a smart helper that learns and grows without us having to give it every little detail. It's like teaching a computer to understand things on its own, making it super adaptable.Now, when we want the computer to understand emotions, we feed it a bunch of examples, like giving it a bunch of stories to learn from. This is our training dataset. We use special tools like CountVectorizer, TF-IDF Transformer, and MLClassifier to teach the computer how to connect the dots and predict emotions in new stories it hasn't seen before.The cool part? We didn't start from scratch. We used ready-made models for both traditional machine learning (ML) and fancy deep learning (DL). It's like having expert friends who already know a lot about predicting emotions. For ML, we had buddies like Decision Trees (DT), Support Vector Machines (SVM), Naive Bayes (NB), and Random Forest (RF). On the deep learning side, we had our pals Gated Recurrent Unit (GRU), Bidirectional Gated Recurrent Unit (Bi-GRU), and Convolutional Neural Network (CNN).

3.5.1. Gated Recurrent Unit (GRU). Imagine a standard recurrent neural network (RNN) as a student trying to learn from examples, like reading a story. Now, this student has a problem – the vanishing gradient problem. It's like when you're reading a really long story, and after a while, the details from the beginning start fading away. This happens to the computer too, where it forgets important stuff from the past.
To help our student (or computer) with this memory issue, we introduce a superhero called the Gated Recurrent Unit (GRU). It's like a special technique that prevents our student from forgetting too much, making sure the lessons from the start of the story stick around until the end. The GRU and its cousin, the Long Short-Term Memory (LSTM), are kind of like two study methods – they are similar and both work really well.
In our proposed model, the GRU is like a smart friend in the group. It's a single layer, which means it's focused on understanding one part really well. After our computer learns the important features from the story, it uses this GRU model to predict the emotions in the data. So, it's like our student having a trustworthy friend who helps remember all the crucial details in a story, making the understanding of emotions even better.

3.5.2. Bidirectional Gated Recurrent Unit (Bi-GRU). Alright, let's imagine the Bidirectional GRU (Bi-GRU) as a dynamic duo in a storytelling club. Picture two friends, one named Forward Fred and the other Backward Benny. These buddies work together to understand the sequence of events in a story. Forward Fred listens to the story from the beginning to the end, while Backward Benny listens from the end to the beginning.Now, these friends are smart – they only focus on what's important. They have these cool input and output gates that filter out the less crucial details. It's like when you're telling a story to a friend, and you both catch the highlights without getting bogged down in every little thing.In our storytelling club, the Bi-GRU is like a single layer – a concentrated effort to understand the story from both ends. So, when our computer is trying to predict emotions from a story, it's like having this pair of attentive friends, one walking from the start, and the other from the end, meeting in the middle to grasp the complete picture. It's a teamwork approach that makes understanding emotions in a sequence even more effective. After feature extraction, the embedding layer of size (18210, 300) will be input for the Bi-GRU model shown in Figure 6. The training vector will be given as an input into the Bi-GRU model to predict the emotions for the data.

3.5.3. Convolutional Neural Network (CNN). It is a form of deep neural network used to analyse visual imagery in deep learning [26]. The CNN model is of a single layer in our proposed model. After feature extraction, the em- bedding layer of size (18210, 300) will be input for the CNN model shown in Figure 7. The training vector will be input into the CNN model to predict the emotions for the data [27].

3.6. Hybrid Model. The proposed hybrid model combines deep learning and machine learning algorithms to predict emotions. The overall system diagram is shown in Figure 8. Deep learning consists of CNN and Bi-GRU, and machine learning consists of an SVM classifier. It starts with input datasets, which are fed into the word embedding layer, i.e., word2vec. After getting the embedding vector, it needs to be fed into both the deep learning algorithms, namely, CNN and Bi-GRU. From CNN and Bi-GRU models, we have removed the last layer, and so they will act as encoders [28].Furthermore, both of these encoders will generate a latent vector for the given input embedding vector. Lastly, these latent vectors will be concatenated and will be fed to the SVM classifier. The SVM classifier will predict the emotion of these input texts.The proposed hybrid model gives improved results in terms of accuracy and F1 score due to the selection of classification models in both deep learning and machine learning. In the individual results of deep learning models, CNN and Bi-GRU performed well. Similarly, in the machine learning algorithms, SVM performed well [29]. There- fore, we choose the best classifiers from both categories to improve the result. In the hybrid model, we combined the ML and DL models, as shown in Figure 8. So, we combined the two best deep learning models, which give the best accuracy and F1 score. After getting the best DL models, the latent vector was given as an input to the best ML models, which predicts emotions as it shows high accuracy [30].

4. Results and Discussion

In our extensive experimental endeavors, we pursued heightened accuracy for our proposed emotion classification model by employing various methodologies. These methods encompassed a machine learning (ML) approach, a deep learning (DL) approach, and a hybrid model combining elements of both on a multitext dataset containing sentences, tweets, and dialogs. For the ML approach, we utilized a pipeline where the input text was converted into vectors, subsequently employed to train an ML classifier. The resulting accuracy, detailed in Table 2, reflects the performance of our ML model. In the DL approach, features were extracted using a pretrained word vector, and the DL model, operating on a padded vector with an input layer of an embedding matrix (18210, 300), was trained. Table 3 illustrates the accuracy of the DL models. Our hybrid model amalgamates ML and DL by combining a DL model with both Convolutional Neural Network (CNN) and Bidirectional Gated Recurrent Unit (Bi-GRU), generating a latent vector. This vector serves as input for an SVM model during training, as depicted in Table

TABLE 2: Evaluation matrix for ML Classifiers

ML classifier	Precision	Recall	F1 score	Accuracy
SVM	**81.45**	**78.36**	**79.67**	**78.97**
RF	79.42	75.66	77.02	76.25
NB	61.75	51.41	49.61	68.94
DT	72.48	69.70	70.94	69.42

TABLE 3: Evaluation matrix for with DL model.

Deep learning	Precision	Recall	F1 score	Accuracy
GRU	78.37	78.94	78.65	78.02
Bi-GRU	80.62	79.64	80.09	**79.46**
CNN	**82.12**	**79.92**	**80.76**	79.32

TABLE 4: Evaluation matrix for our hybrid model.

Hybrid	Precision	Recall	F1 score	Accuracy
CNN + Bi-GRU + SVM	**82.39**	**80.40**	**81.27**	**80.11**

4.Comparing the basic ML and DL models, we observed improved results individually, yet neither achieved optimal accuracy. Notably, the ML approach excelled in accuracy across different emotions, as did the DL approach. By integrating these models into a hybrid framework, we achieved the highest accuracy. Emotion detection from text remains an intricate challenge due to the absence of explicit emotional expressions and the nuanced structure of textual sentences. While researchers have made significant strides in facial emotion expression and speech emotion recognition, a comprehensive solution for text-based emotion detection remains elusive, representing an ongoing mystery in this research domain.

5. Conclusion and Future Direction

This paper introduces a novel text-based emotion recognition model that seamlessly blends deep learning and machine learning methodologies, leveraging the strengths of both paradigms. The hybrid model is designed to operate across diverse datasets, namely ISEAR, WASSA, and the Emotion-Stimulus dataset, offering versatility in handling multitext inputs such as sentences, tweets, dialogs, keywords, and emotion-centric lexicon words. Notably, the machine learning component, employing the Support Vector Machine (SVM) classifier, attains a commendable accuracy of 78.97%. On the deep learning side, the Bidirectional Gated Recurrent Unit (Bi-GRU) model outperforms others with an accuracy of 79.46%, while the Convolutional Neural Network (CNN) model achieves an impressive F1-score of 80.76. The hybrid model exhibits a well-rounded performance, boasting a precision of 82.39, a recall of 80.40, an F1 score of 81.27, and an overall accuracy of 80.11%.Looking ahead, our research agenda includes exploring additional classifiers and ensemble techniques to further refine the model's efficacy. In the realm of deep learning, we aim to experiment with combinations involving CNN, Bi-GRU, and Long Short-Term Memory (LSTM) to unlock potential performance enhancements. Furthermore, we plan to delve into the structural nuances of text sentences, incorporating considerations for regional languages to broaden the model's applicability. In the context of our increasingly digital society, characterized by the prolific generation of text data through messaging, tweeting, and online product reviews, we envision the development of a real-time text-based emotion recognition model. Such an endeavor holds the promise of capturing the authentic emotions and moods of individuals in real-world scenarios, thereby contributing to a more humane and contextually aware digital interaction landscape.

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