International Research Journal of Multidisciplinary Sciences ISSN:3107-930X(ONLINE)
VOL-2 ISSUE-2 February 2026 PP:1-9

A Review on Enhancing Social Media Emotion Analysis from Noisy Text Using Deep Learning

[1]Deepak Goswami,[2]Shyamol Banerjee

[1]M.Tech Student, Dept. of CSE, SRCEM, [2]Assistant Professor, Dept. of CSE, SRCEM

[1]contactdeepakgoswami@gmail.com, [2]shyamolgwl@gmail.com

***Abstract*--This review looks at how far we've come in figuring out how to discern emotions in noisy internet writing using deep learning methods.Social media sites provide huge amounts of unstructured data, like slang, acronyms, emoticons, and text in more than one language. This makes it very hard for traditional natural language processing models to work. To deal with these problems, other deep learning methods have come up, notably CNNs, RNNs, and transformer-based models like BERT and GPT. These models are great at picking up on subtle differences in context and meaning, which makes it easier to classify emotions. Attention techniques and hybrid model architectures help performance even more by focusing on important text elements and reducing noise interference. Also, multimodal models that include text, audio, and visual data can give a whole picture of how someone is feeling. Results from different research that compare transformer-based models to traditional methods reveal that transformer-based models work far better, especially in noisy environments. Even with these improvements, there are still problems with things like data imbalance, model interpretability, and scalability. This review also talks about how data augmentation and domain adaptation might help models work better in general. Future research must prioritize the advancement of explainable AI systems, cross-lingual models, and real-time applications to guarantee effective and inclusive emotion detection solutions. These methods are useful in the actual world, as shown by their use in mental health monitoring, customer sentiment analysis, and predicting social behavior. This review offers significant insights into the evolving domain of emotion identification from noisy social media data through advanced deep learning techniques by combining current advancements and pinpointing critical hurdles.**

Keywords-Emotion Detection, Noisy Text Data, Social Media, Deep Learning

I. INTRODUCTION

People use social media every day to talk to each other because it helps them express their opinions, emotions, and observations. But the large amount of information made by users on sites like Facebook, Twitter, and Instagram can sometimes involve loud, casual, and unstructured text. This data is incredibly hard to read because it is full of slang, acronyms, emoticons, and grammar mistakes. Many applications, such as sentiment analysis, mental health monitoring, client feedback analysis, and studies of social behavior, require to know how the data they are consuming makes them feel. Conventional natural language processing (NLP) methodologies rely on rigid linguistic structures and a limited comprehension of context, rendering them ineffective in accurately discerning emotions from noisy data. Recent progress in deep learning has shown promise in improving recognizing feelings from social media text by employing large datasets and advanced neural network architectures to overcome current constraints. Emotion detection is the process of finding and grouping emotions in text data. Emotion detection looks into more complex emotions like anger, happiness, sadness, fear, or surprise. Classical sentiment analysis, on one hand, just searches for polarity and puts text into three groups: positive, negative, or neutral. To achieve this degree of specificity in emotional classification, it is essential to utilize strong models capable of detecting both overt and nuanced emotional cues. In this context, deep learning models, especially convolutional neural networks, recurrent neural networks, and transformers, have shown exceptional effectiveness[1], [2]. These algorithms are useful for figuring out how one feels since they can collect semantic, syntactic, and context-specific data from noisy social media posts. It's challenging to work with social media data because it's not official and doesn't always use the same words. Code-switching is when someone use more than one language in the same post. This is how they usually express themselves. This thing called Hinglish makes it a lot harder to figure out how you feel in places like India.

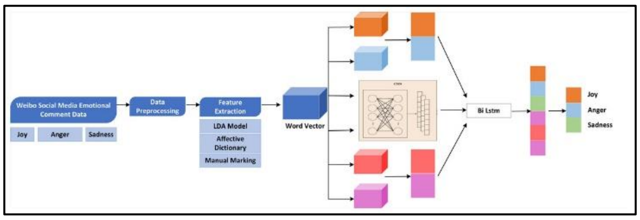

Fig. 1 Emotion Recognition on social Media [3]

Sarcasm, irony, and imprecise language require models to accurately discern the underlying emotional significance. Deep learning algorithms with advanced attention mechanisms and contextual embeddings can help get around these problems by looking at text as a whole. We can now identify emotions in a new way thanks to word embeddings, contextualized models of language like BERT (Bidirectional Encoder Representations from Transformers), or pre-trained transformer models. These models can genuinely understand context, semantics, and tone. Preparing the data is often what makes machine learning algorithms better at figuring out how people feel.Strategies for reducing noise, such as interpreting emojis, standardizing slang, and correcting spelling, are what clean and normalize the input text. By producing different training examples, tokenization and text augmentation help to increase model generalization even further. Furthermore relevant labeled data for supervised learning techniques are sentiment lexicons and emotion-specific datasets. In noisy text environments, pre-trained model fine-tuning and transfer learning also greatly improve accuracy and robustness[4]–[6]. Domain-specific datasets Emotion identification from noisy text data finds extensive and significant uses. Emotion detection systems can help in the healthcare field by means of social media post analysis to detect symptoms of mental health diseases including depression and anxiety. For media organizations, companies, and legislators, real-time public opinion tracking of political events, crisis, or product introductions offers insightful analysis. Moreover, automated emotional analysis helps customer support systems respond personally and raises client satisfaction by means of tailored responses. By allowing sympathetic and context-aware conversations, the integration of emotional detection in chatbots and virtual assistants further enhances user experience. Developing scalable and interpretable deep learning models for emotion detection still presents difficulty notwithstanding the progress. Biased predictions could happen if there is an imbalance in the data, which means that some emotions are not reflected enough. Explainability and openness are vital for gaining user trust and making sure that AI is used ethically in deep learning models. Future research should focus on developing hybrid models that enhance interpretability and generalization by integrating knowledge based methodology with deep learning. Another interesting way to get deep emotional insights from social media is to use multimodal emotion recognition, which looks at text, photos, and speech. Deep learning can help AI work better in a lot of areas by making it easier to recognize emotions in noisy text data. Researchers and practitioners can create strong emotion detection systems that support improved comprehension and response to human emotions in the digital age by tackling the complexity of social media language and using state-of-the-modern neural network designs. Emotion detection systems' efficacy and applicability will be further driven by ongoing developments in model development, data preprocessing techniques, and ethical artificial intelligence practices, therefore promoting a more emotionally intelligent technology environment.

II. LITERATURE REVIEW

Dui 2024 et al. While social media rapidly disseminates erroneous information and rumors, therefore enabling public panic and societal instability by means of its speedy spreading of knowledge. Conventional multimodal sentiment analysis approaches suffer in efficiently combining elements from several modalities, therefore lowering classification accuracy. Using the Transformer's encoding layer to extract sentiment semantics from audio and text input, a new emotion classification model is proposed to solve this. Capturing intra- and intermodal correlations helps a bimodal feature interaction fusion attention technique to improve understanding even more. This enhanced fusion strategy raises the capacity of the model to understand emotions. Ranked on the IEMOCAP dataset, the model beats all others with an F1-score of 77.6% and a classification accuracy of 78.5%. These results demonstrate the model's proficiency in comprehending discourse emotions, consequently facilitating social network behavior monitoring and enhancing public sentiment security management [7].

Ahmed 2024 et al. Textual emotional awareness improves understanding of human interaction. Even though a lot of study has been done on English sentiment analysis, Bengali still doesn't get as much attention. This research examines the variation of emotions in Bengali social networking messages through a dataset of seven sensations: Happy, Surprise, Fearful, Furious, Neutral, Disgust, and Sad. Some of the machine learning models used were support vector predictive models, decision trees, logistic regression, or random forest. The answers were right 84% of the time for Random Forest.The findings endorse sentiment analysis, psychoanalysis, and communication technology by elucidating Bengali emotional expression, hence facilitating their applications. This study expands emotional analysis by tackling language complexity and promotes further research across other domains[8].

Geethanjali2024 et al. Multimodal sentiment analysis assists in understanding public opinion during events like COVID-19. It suggests a hybrid model called IChOA-CNN-LSTM that uses Convolutional Neural Networks (CNNs) for extracting visual features, Long Short-Term Memory (LSTM) networks for analyzing sequential data, and an Improved Chimp Optimization Algorithm for fusing features. It is better than traditional methods because it is around 97.8% accurate. The research uses the GeoCoV19 dataset to talk about how people around the world are talking about the pandemic in different languages and places. A comprehensive approach improves public health decision-making by elucidating the intricate interplay of emotions during emergencies, so substantially advancing the domain of multimodal sentiment analysis[9].

Velmurugan 2023 et al. You can show how you feel by speaking, writing, using your face, and making gestures. Writing makes it hard to get those feelings out. The goal of the research is to use machine learning to get emotions from social media word data. Raw text is often not useful, so preprocessing is necessary to make the data better and give insights. Our method improves the accuracy of emotion detection by using strict preprocessing. The results give stakeholders a deeper understanding of people's thoughts and feelings at certain times, which helps them make better decisions in many areas, such as marketing, public opinion research, and behavioral research[10].

Guo 2022 et al. Emotion identification is a basic subject that uses speech, facial expressions, writing, and gestures to help people understand their feelings. We suggest Deep Learning Assisted Semantic Text Analysis for recognizing human emotions in large amounts of data. The method gathers semantic and syntactic text features using word embeddings and Natural Language Processing (NLP). Results indicate a 97.22% emotional detection rate and a 98.02% classification accuracy, surpassing existing approaches. Better emotional word embeddings can help improve accuracy even more. They have important uses in sentiment analysis, human-computer interaction, and psychological testing[11].

TABLE 1 LITERATURE SUMMARY

Authors/years	Methodology	Research gap	Findings
Khan/2022 [12]	Emotion-based DNN detects cyber aggression.	Lack of emotional features in cyber aggression detection models.	Proposed DNN achieved 97% F1 score, outperforming existing models.
Aldhyani/2022 [13]	CNN-BiLSTM excels in suicidal detection.	Limited use of LIWC features in suicidal ideation detection.	CNN-BiLSTM achieved 95% accuracy, outperforming XGBoost with text features.
Alsayat/2022 [14]	LSTM ensemble enhances sentiment classification accuracy.	Lack of robust sentiment analysis in emerging situations.	Ensemble LSTM model outperformed others in sentiment classification accuracy.
Murshed/2022 [15]	SMDCM enhances short-text topic modeling.	Limited data quality improvement methods for short-text topic modeling.	SMDCM improved topic coherence and accuracy using GLTM and WNTM.
Riza/2021 [16]	LSTM with FastText improves emotion detection.	Limited accuracy due to insufficient data and model variety.	Word2Vec and FastText achieved 73.15% accuracy in emotion detection.

III. IMPORTANCE OF EMOTION DETECTION IN SOCIAL MEDIA

In the digital age, figuring out how individuals feel on social networks has become an important component of figuring out how they act and think. Not only do people use Facebook, Twitter, and Instagram to connect to each other, but they are also massive collections of content contributed by users that show how people think, feel, and what they want to say[17]. Legislators, businesses, and researchers can utilize this data to make better decisions by looking at it.

- Enhancing Brand Management and Marketing

Companies can use emotion detection to keep an eye on how people feel about their products, services, or marketing initiatives. Businesses may figure out how people feel about their brand and how happy they are with it by looking at user comments and ratings and seeing if they are favorable, negative, or neutral. Businesses may adjust their marketing strategy, deal with customer concerns, and personalize their communications with customers in real time, which builds brand loyalty. It also gives you a good look at how people act, what they like, and what new trends are coming up. Businesses can predict how customers would react, improve product development, and make commercials that are more interesting. This proactive approach to sentiment analysis improves relationships with customers, gives you a competitive edge, and makes it feasible to make decisions based on facts for continuous business growth[18].

- Understanding Public Opinion

Emotion detection is used by media businesses, lawmakers, and governments to keep an eye on how people feel about laws, movements, or events. Watching how people react emotionally on social media shows how people feel about things and what they care about. This information is very useful since it has an impact on how policies are made, how crises are handled, and how decisions are made. By looking at emotional tendencies, authorities may figure out where instability is most likely to happen, quickly respond to public complaints, and improve their communication techniques. Also, being conscious of your feelings might help you figure out how the public feels about changes to the law and how well government programs are working. These kinds of insights help the government be more honest, make better decisions, and give people more faith in institutions [19].

- Supporting Mental Health Initiatives

Social media is being used more and more to keep an eye on people's mental health since it can pick up on how people are feeling. When you analyze text data, algorithms can find signals of emotional distress, despair, or thoughts of suicide. Researchers and mental health groups may use this information to quickly find solutions, give help, and organize enhanced psychological awareness campaigns. Also, medical experts can learn more about mental health patterns by keeping track of emotional trends in real time.

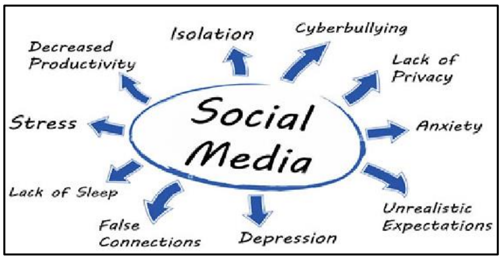

Fig. 2 Supporting Mental Health Initiatives [20]

Policymakers can also create focused programs based on emotional insights. This technology helps people with mental health problems get the help they need and lowers the stigma around them. This encourages people to take a proactive approach to mental health care[21].

- Combating Cyberbullying and Toxicity

Cyberbullying and online abuse can cause a lot of problems in the digital world. Emotion detection technologies enable platforms find and get rid of harmful content by finding angry or toxic words. Real-time moderation systems that use emotional identification make online spaces safer and encourage better digital interactions. You may also utilize similar ideas on platforms to warn people about and check out potentially hazardous content before it becomes popular. By using emotional pattern analysis of devices that can detect emotions, you may learn about how users behave and help with proactive intervention tactics. These kinds of fixes safeguard vulnerable consumers, lower the prevalence of cybercrime, and help make the internet a more welcoming and civilized place [22].

- Personalizing User Experience

Emotion recognition algorithms on social media sites help make each user's experience unique. By looking at how users engage with and take in content, platforms can offer relevant content, adverts, and services based on their emotional states. This level of customization makes users more involved and happy. Depending on how you feel, platforms can also modify alerts, suggest friends, or put up news feeds.If platforms know how consumers feel, they can better guess what they want, make their algorithms better, and deliver them more meaningful experiences. Also, emotional assessment makes sure that visitors only receive material that fits with how they feel and what they're interested in right now. This helps advertisers contact the right people with greater efficiency and makes ads more useful [23].

IV. ROLE OF NATURAL LANGUAGE PROCESSING IN EMOTION DETECTION

Natural language processing is an aspect of AI that helps machines understand and process what people say. It can figure out how people are feeling deep down, like joyful, sad, furious, or terrified, by looking at text data. This helps them grow emotionally. NLP uses the most advanced algorithms to analyze a lot of data from places like social media postings, comments, and product reviews. NLP systems use linguistic patterns, subtle differences in feelings, and signals from the situation to sort emotions correctly. This skill makes it easier to figure out what others think, keep a watch on mental health, and look at what customers say. This gives corporations, scholars, and policymakers vital information that helps them make choices [24].

- Text Preprocessing for Emotion Detection

Natural language processing (NLP) techniques get data ready for analysis by cleaning up the text as needed, which makes the model more accurate. Tokenizing text breaks it up into separate words or phrases so that it may be processed more easily. Stopwords are common words like "and," "the," or "is" that don't change the meaning of a sentence. Lemmatization changes words into their base forms as they are in the dictionary. Stemming trims words down to their root forms by taking off suffixes. These processes make sure that textual data is consistent, reduce the number of duplicates, and make sure that feature extraction is done quickly. NLP models can better understand emotions, attitudes, and contextual meanings in many applications by improving text with these methods [25].

- Sentiment and Emotion Classification

Sentiment analysis and emotional classification are important uses of Natural Language Processing (NLP) that put text into pre-defined emotional categories like happiness, sadness, fury, or fear.

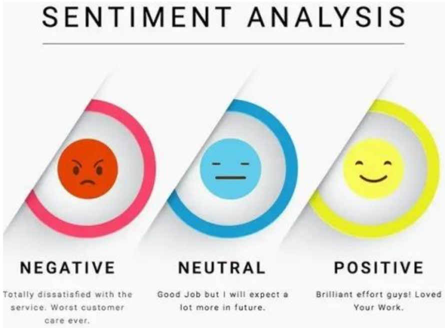

Fig. 3 Sentiment and Emotion Classification [26]

These models identify underlying emotions using textual input employing various ways. Neural Networks, such Recurrent Neural Networks (RNNs) and CNNs, are great at finding complicated patterns and meanings in context. Support Vector Machines (SVMs), on the other hand, are frequently utilized because they operate well in high-dimensional spaces. Businesses and companies will be able to better understand customer feedback, social media posts, and surveys by using these models. This will lead to better decision-making based on data and better user experiences [27].

- Word Embedding Techniques

Natural language processing (NLP) can use word embedding methods like Word2Vec, GloVe, and FastText to turn words into numerical vectors while keeping their meaning and how they relate to other words. Word2Vec employs neural networks to make word embeddings depending on the words around them, while GloVe looks at how often words appear together to make useful representations. FastText makes this better by giving information about subwords, which helps make sense of strange and misspelled phrases. These embeddings help algorithms understand the subtleties of language, which makes it easier to find patterns in text-based emotion detection. This is the kind of skill you need to look at social media posts, client reviews, and comments [28].

- Multilingual Emotion Detection

Using language-specific tools and multilingual word embeddings like MOSE, LASER, and XLM, natural language processing (NLP) may find emotions in more than one language. These embeddings assist models understand and interpret emotions correctly by making semantic linkages between different languages. NLP systems can figure out how emotional something is in various languages without a lot of labeled data by using translation models, cross-lingual embeddings, and transfer learning. Global platforms that keep an eye on public opinion, social media trends, and customer opinions across many language groups are especially valuable. Multilingual emotion identification and more accurate sentiment analysis make it easier to distribute personalized material and make decisions because they can reach a lot more people [29].

- Applications in Real-Time Emotion Monitoring

Many fields use real-time emotional detection in natural language processing (NLP) to make quick decisions. NLP systems examine at user comments, posts, and trends on social media to figure out how people feel and find problems that are getting worse. Using real-time emotional detection, businesses look at what customers say, find out what makes them unhappy, and respond immediately to make them happier. In times of crisis, NLP also helps governments and businesses keep an eye on public opinion, look at people's emotional responses, and make judgments based on what they find. This proactive study can make quick fixes, better customer service, and better crisis management plans by using real-time information that can be acted on [30].

V. APPLICATIONS OF EMOTION DETECTION IN SOCIAL MEDIA

In brand monitoring, customer service, mental health support, cyberbullying identification, and political analysis, emotional detection is absolutely essential. It lets companies improve happiness, personalize user experiences, and evaluate public opinion. Mental health groups apply it in timely interventions. Platforms provide safer interactions by identifying damaging material. For wise decision-making, governments measure public opinion[31].

1. Brand Monitoring and Sentiment Analysis

Social media consumer opinion analysis supports brand monitoring and significantly depends on emotional identification. Companies use it to learn public impressions of their campaigns, products, or offerings. Through comments, evaluations, and discussions, companies can identify areas of development, project possible difficulties, and change their marketing strategies by means of emotional reaction analysis. Although negative opinions provide information for product development, good comments supports successful advertising. Emotional detection keeps companies competitive by continually knowing consumer preferences and tailoring their offerings to match evolving customer wants[32].

2. Customer Service and Engagement

Emotion detection improves customer service by giving businesses an idea of how customers feel about their interactions or offers. Businesses may quickly fix problems and influence people's minds by looking at comments, criticism, and complaints. By predicting what customers will want based on their emotional tone, it helps businesses create one-of-a-kind experiences. Chatbots that can sense emotions can respond in a way that makes customers happier. Businesses can build stronger relationships with customers by proactively engaging with them based on real-time sentiment research. This leads to brand loyalty and a strong brand image [33].

3. Mental Health and Well-Being Support

A lot of the time, social media sites let people share their feelings. Emotional detection technology looks through content made by users for symptoms of melancholy, anxiety, or depression. Researchers and mental health groups can support people and act quickly when they see these emotional changes. You can find major mental health problems or thoughts of suicide by looking at the emotional signals in text data. Emotional detection systems also help raise awareness about mental health by finding common emotional issues in certain locations and suggesting the right tools or support networks.

4. Cyberbullying and Content Moderation

To keep online spaces safe, you need to be able to spot cyberbullying, harassment, or hate speech. This is why emotional detection is so important. These technologies are used on platforms to highlight content that contains dangerous, damaging, or violent language. Real-time monitoring and moderation systems make it easy to quickly remove hazardous content, which lowers the risk to users' mental health. Emotion recognition technology help law enforcement crack down on offenders by spotting patterns of violent conduct. These tools help make online communities more welcoming and polite by encouraging better digital interactions [34].

5. Political and Social Insights

Governments, politicians, and the media might employ emotional detection to find out what people think about elections, policy choices, or big social events. You may adjust your communication strategy by keeping an eye on what people are saying on social media, public opinion, and trend forecasts. Emotion detection offers insightful analysis of societal issues, thereby guiding leaders in their judgments and choices. It also makes advertising that use emotional manipulation or false information clearer. Real-time emotional analysis helps authorities quickly respond to public concerns and keep the peace, which is good for crisis management [35].

VI. REAL-WORLD APPLICATIONS OF EMOTION DETECTION SYSTEMS

Emotion detection systems help companies make their products and services better by looking at reviews and social media to see how people feel about them. This makes the experience better for customers. They assist mental health professionals find emotional discomfort quickly so they can treat it [36]. These tools are used on social networking sites to keep bad content in check and make sure that interactions are safer. Companies utilize these systems to keep track of how customers react and to do market research that helps them plan their marketing. Policymakers utilize emotional awareness to keep track of what people think about events and policies, which helps them make decisions. Real-time information from many fields benefit businesses and society by letting people become involved in their own way, handle crises, and create pleasant online spaces.

1. Customer Experience Enhancement

Emotion detection systems look at the feelings that people express in surveys, comments on social media, and reviews. This makes the experience better for customers. These technologies help businesses figure out what customers like, what bothers them, and how happy they are with the service. Businesses can change their products, services, and marketing methods to fulfill customer expectations if they can tell whether someone is happy, angry, or disappointed. Businesses can quickly fix problems, handle complaints, and give personalized help with real-time analysis. Emotion detection can also help find patterns of displeasure that point to problems with the quality of items or services. If businesses work hard to improve their products and services, they can keep customers happy and loyal. Businesses and customers can become closer to each other by getting personalized advice and targeted interaction. Also, businesses may predict trends, improve their marketing strategies, and stay ahead of the competition by keeping an eye on how customers feel all the time. In the end, using emotional detection technologies improves the whole consumer experience, builds brand loyalty, and helps the organization succeed in the long run [37].

2. Healthcare and Mental Health Support

Healthcare is using emotional detection technologies to help mental health practitioners keep track of their patients' emotional states through social media posts, online interactions, and text data. By looking at language patterns and emotional indicators, these systems can find signs of emotional pain, anxiety, despair, or thoughts of suicide. Doctors can intervene quickly, give the right psychological support, and help avoid probable tragedies if they find out about them early. Telehealth apps use emotional detection to give personalized care by proposing the right therapy materials, self-help tools, or counseling services based on how a patient is feeling. Virtual mental health technology can also leverage these outcomes to their advantage by providing ongoing monitoring, which makes sure that patients always have access to help [38]. Emotion detection also helps academics study mental health patterns in different groups of people, which helps them make better mental health campaigns. Adding emotional awareness to telehealth services helps healthcare professionals get better treatment results, get patients more involved, and improve mental health in general.

3. Social Media Monitoring and Moderation

Emotion detection algorithms are becoming more and more important on social media sites for finding and getting rid of bad content like cyberbullying, hate speech, and harassment. These algorithms can find indicators of anger, hatred, or aggression by looking at the emotional tone of user-generated data. Advanced algorithms let platforms find and remove inappropriate or abusive content right away by letting them look at text data in real time. This proactive strategy not only protects consumers from mental harm, but it also encourages safer and better online connections [39].

Fig. 4 Social Media Monitoring and Moderation [40]

Automated moderation approaches make it easier to enforce community standards all the time, which helps stop the spread of bad tales. Also, being aware of how toxic behavior makes others feel helps platforms spot patterns of harmful behavior. This lets them take steps to stop it, including banning or suspending accounts that are responsible for harassment. These systems help make the internet a more welcoming and inviting place by encouraging polite interactions. Social media firms will also benefit greatly from learning about new online behavior patterns because it will let them change and strengthen their moderation practices.

4. Market Research and Brand Analysis

Companies can stay up to date on changes in their field and how customers feel about them thanks to emotion-detecting devices. Businesses may figure out if people have good, negative, or neutral feelings about their brand announcements, ads, and new products by looking at the responses. Companies may use this real-time data to make sensible, fact-based choices that will improve their marketing plans and make sure they are still relevant to their target market. Also, being able to recognize emotions lets businesses guess what customers will want and adapt their products or services to keep up with current trends. Companies may reduce the damage to their reputation and make their customers happier by dealing with unfavorable attitudes right away. Companies can also look at the emotional impact of commercials and marketing tools to see how well a campaign is doing and how well the brand is resonating. Businesses can learn about how people act by looking at the sentiment of polls, product reviews, and comments on social media. In a fast-paced world, being able to recognize emotions eventually improves customer relationships, brand loyalty, and a company's ability to compete [41].

5. Political and Social Sentiment Analysis

Governments and lawmakers who want to know what people think about social issues, elections, and policy are finding that emotion detection technology are becoming more useful. These systems give real-time public opinion by using sentiment analysis of social media, forums, and online debates. This information helps politicians understand how people feel, what problems they have, and how they react to government activities[42]. Emotion detection helps candidates adjust their message by giving them useful feedback on how well their campaign is doing, how popular they are, and what new issues are coming up during elections. During a crisis, such as a natural disaster or political upheaval, governments may quickly find out what people think so they can respond correctly and clear up any false information. Emotion detection shows how accountability and openness are changing, which helps us figure out how new rules affect how people feel about things. With these insights, authorities may improve public trust, improve communication methods, and make decisions based on facts. The ability to recognize emotions is fundamental to effective governance and prudent policy formulation[43]–[45].

VII. CONCLUSION

In summary, enhancing emotion recognition from noisy social media text data remains a challenging endeavor in the field of natural language processing. The natural complexity of unstructured data, such as slang, acronyms, emoticons, and grammatical errors, makes it hard to accurately recognize emotions. We need modern deep learning models since traditional methods don't always catch the subtle ways that people express themselves. Convolutional neural networks (CNNs), retinal neural networks (RNNs), and transformer-based designs have all made significant strides in understanding the contextual and semantic importance of text. These algorithms can find little emotional indicators more accurately by using large datasets, which makes detection more accurate. Also, using hybrid models and focus processes has helped to reduce noise interference while focusing on important text parts. Pretrained language models like BERT and GPT have made categorization systems even more resilient by setting new criteria for emotional detection. Multimodal approaches that combine text, images, and sound data can also give a full picture of emotional states. Utilizing data augmentation and explainable artificial intelligence methodologies to tackle challenges such as data imbalance, class overlap, and model interpretability enhances detection outcomes. Future research ought to examine low-resource and cross-lingual contexts to enhance the inclusivity of emotional detection systems. Adding information that is relevant to a certain field and processing data in real time can also make social behavior research, consumer sentiment analysis, and mental health monitoring more useful. Eventually, deep learning will keep getting better and better, which will lead to the development of emotion recognition algorithms that are more accurate, scalable, and adaptable in noisy social media contexts.

REFERENCES

[1] B. Tasci, “Deep Learning-Based Detection of Depression and Suicidal Tendencies in Social Media Data with Feature Selection,” 2025.

[2] J. Yan, P. Pu, and L. Jiang, “Emotion-RGC net: A novel approach for emotion recognition in social media using RoBERTa and Graph Neural Networks,” *PLoS One*, vol. 20, no. 3, p. e0318524, 2025, doi: 10.1371/journal.pone.0318524.

[3] “Emotion Recognition on social Media - - Image Search results.” https://in.images.search.yahoo.com/yhs/search;_ylt=Awr1SdXKeepnz8E1hBznHgx.;_ylu=Y29sbwMEcG9zAzEEdnRpZAMEc2VjA3BpdnM-?p=Emotion+Recognition+on

[4] C. Yang and Y. Zhang, “Public emotions and visual perception of the East Coast Park in Singapore: A deep learning method using social media data,” *Urban For. Urban Green.*, vol. 94, no. February, p. 128285, 2024, doi: 10.1016/j.ufug.2024.128285.

[5] S. R. Naher, S. Sultana, T. Mahmud, M. T. Aziz, M. S. Hossain, and K. Andersson, “Exploring Deep Learning for Chittagonian Slang Detection in Social Media Texts,” *Int. Conf. Electr. Comput. Energy Technol. ICECET 2024*, no. October, 2024, doi: 10.1109/ICECET61485.2024.10698491.

[6] H. H. Nguyen, “Enhancing Sentiment Analysis on Social Media Data with Advanced Deep Learning Techniques,” *Int. J. Adv. Comput. Sci. Appl.*, vol. 15, no. 5, pp. 970–980, 2024, doi: 10.14569/IJACSA.2024.0150598.

[7] Y. Dui and H. Hu, “Social Media Public Opinion Detection Using Multimodal Natural Language Processing and Attention Mechanisms,” *IET Inf. Secur.*, vol. 2024, no. 1, 2024, doi: 10.1049/2024/8880804.

[8] M. Ahmed, A. Sobhan, M. S. Hossen Sajib, and N. Masud, “Investigation Emotion Dynamics in Bangla Social Media Text for Improved Emotion Detection,” *2024 IEEE Conf. Comput. Appl. Syst. COMPAS 2024*, no. September, 2024, doi: 10.1109/COMPAS60761.2024.10795978.

[9] R. Geethanjali and A. Valarmathi, “A novel hybrid deep learning IChOA-CNN-LSTM model for modality-enriched and multilingual emotion recognition in social media,” *Sci. Rep.*, vol. 14, no. 1, p. 22270, 2024, doi: 10.1038/s41598-024-73452-2.

[10] T. Velmurugan and B. Jayapradha, “Emotion Deduction from Social Media Text Data Using Machine Learning Algorithm,” *J. Comput. Commun.*, vol. 11, no. 11, pp. 183–196, 2023, doi: 10.4236/jcc.2023.1111010.

[11] J. Guo, “Deep learning approach to text analysis for human emotion detection from big data,” *J. Intell. Syst.*, vol. 31, no. 1, pp. 113–126, 2022, doi: 10.1515/jisys-2022-0001.

[12] U. Khan, S. Khan, A. Rizwan, G. Atteia, M. M. Jamjoom, and N. A. Samee, “Aggression Detection in Social Media from Textual Data Using Deep Learning Models,” *Appl. Sci.*, vol. 12, no. 10, 2022, doi: 10.3390/app12105083.

[13] T. H. H. Aldhyani, S. N. Alsubari, A. S. Alshebami, H. Alkahtani, and Z. A. T. Ahmed, “Detecting and Analyzing Suicidal Ideation on Social Media Using Deep Learning and Machine Learning Models,” *Int. J. Environ. Res. Public Health*, vol. 19, no. 19, 2022, doi: 10.3390/ijerph191912635.

[14] A. Alsayat, “Improving Sentiment Analysis for Social Media Applications Using an Ensemble Deep Learning Language Model,” *Arab. J. Sci. Eng.*, vol. 47, no. 2, pp. 2499–2511, 2022, doi: 10.1007/s13369-021-06227-w.

[15] B. A. H. Murshed, J. Abawajy, S. Mallappa, M. A. N. Saif, S. M. Al-Ghuribi, and F. A. Ghanem, “Enhancing Big Social Media Data Quality for Use in Short-Text Topic Modeling,” *IEEE Access*, vol. 10, no. October, pp. 105328–105351, 2022, doi: 10.1109/ACCESS.2022.3211396.

[16] M. A. Riza and N. Charibaldi, “Emotion Detection in Twitter Social Media Using Long Short-Term Memory (LSTM) and Fast Text,” *Int. J. Artif. Intell. Robot.*, vol. 3, no. 1, pp. 15–26, 2021, doi: 10.25139/ijair.v3i1.3827.

[17] B. Gaind, V. Syal, and S. Padgalwar, “Emotion Detection and Analysis on Social Media,” 2019, [Online]. Available: http://arxiv.org/abs/1901.08458

[18] M. Krommyda, A. Rigos, K. Bouklas, and A. Amditis, “An experimental analysis of data annotation methodologies for emotion detection in short text posted on social media,” *Informatics*, vol. 8, no. 1, 2021, doi: 10.3390/informatics8010019.

[19] A. S. Uban, B. Chulvi, and P. Rosso, “An emotion and cognitive based analysis of mental health disorders from social media data,” *Futur. Gener. Comput. Syst.*, vol. 124, pp. 480–494, 2021, doi: 10.1016/j.future.2021.05.032.

[20] “social media’s emotional detecting mental health.” https://www.researchgate.net/figure/Effects-of-social-media-on-mental-health_fig3_375974324 (accessed Mar. 31, 2025).

[21] A. Bhaumik, A. Bernhardt, G. A. Katsios, N. Sa, and T. Strzalkowski, “Adapting Emotion Detection to Analyze Influence Campaigns on Social Media,” *Proc. Annu. Meet. Assoc. Comput. Linguist.*, pp. 441–451, 2023, doi: 10.18653/v1/2023.wassa-1.38.

[22] B. G. Bokolo and Q. Liu, “Combating Cyberbullying in Various Digital Media Using Machine Learning,” *Combat. Cyberbullying Digit. Media with Artif. Intell.*, no. November 2023, pp. 71–97, 2023, doi: 10.1201/9781003393061-7.

[23] L. Khan, A. Amjad, K. M. Afaq, and H. T. Chang, “Deep Sentiment Analysis Using CNN-LSTM Architecture of English and Roman Urdu Text Shared in Social Media,” *Appl. Sci.*, vol. 12, no. 5, 2022, doi: 10.3390/app12052694.

[24] A. Hodorog, I. Petri, and Y. Rezgui, “Machine learning and Natural Language Processing of social media data for event detection in smart cities,” *Sustain. Cities Soc.*, vol. 85, no. May, 2022, doi: 10.1016/j.scs.2022.104026.

[25] W. Graterol, J. Diaz-Amado, Y. Cardinale, I. Dongo, E. Lopes-Silva, and C. Santos-Libarino, “Emotion detection for social robots based on nlp transformers and an emotion ontology,” *Sensors (Switzerland)*, vol. 21, no. 4, pp. 1–19, 2021, doi: 10.3390/s21041322.

[26] “Sentiment and Emotion Classification - Google Search.” https://www.google.co.in/search?q=Sentiment+and+Emotion+Classification&sca_esv=f65d9110a0398786&udm

[27] J. Camacho-Collados *et al.*, “TweetNLP: Cutting-Edge Natural Language Processing for Social Media,” *EMNLP 2022 - 2022 Conf. Empir. Methods Nat. Lang. Process. Proc. Demonstr. Sess.*, no. April 2022, pp. 38–49, 2022, doi: 10.18653/v1/2022.emnlp-demos.5.

[28] P. J. Worth, “Word Embeddings and Semantic Spaces in Natural Language Processing,” *Int. J. Intell. Sci.*, vol. 13, no. 01, pp. 1–21, 2023, doi: 10.4236/ijis.2023.131001.

[29] V. Gupta *et al.*, “3MASSIV: Multilingual, Multimodal and Multi-Aspect dataset of Social Media Short Videos,” *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit.*, vol. 2022-June, pp. 21032–21043, 2022, doi: 10.1109/CVPR52688.2022.02039.

[30] B. Subramanian, J. Kim, M. Maray, and A. Paul, “Digital Twin Model: A Real-Time Emotion Recognition System for Personalized Healthcare,” *IEEE Access*, vol. 10, no. August, pp. 81155–81165, 2022, doi: 10.1109/ACCESS.2022.3193941.

[31] S. Ghosal and A. Jain, “Depression and Suicide Risk Detection on Social Media using fastText Embedding and XGBoost Classifier,” *Procedia Comput. Sci.*, vol. 218, pp. 1631–1639, 2022, doi: 10.1016/j.procs.2023.01.141.

[32] T. M. Swe and N. L. Wah, “Emotion detection on social media status in Myanmar language,” *Int. J. Electr. Comput. Eng.*, vol. 13, no. 5, pp. 5653–5661, 2023, doi: 10.11591/ijece.v13i5.pp5653-5661.

[33] F. M. Talaat, E. M. El-Gendy, M. M. Saafan, and S. A. Gamel, “Utilizing social media and machine learning for personality and emotion recognition using PERS,” *Neural Comput. Appl.*, vol. 35, no. 33, pp. 23927–23941, 2023, doi: 10.1007/s00521-023-08962-7.

[34] A. Kumar and N. Sachdeva, “A Bi-GRU with attention and CapsNet hybrid model for cyberbullying detection on social media,” *World Wide Web*, vol. 25, no. 4, pp. 1537–1550, 2022, doi: 10.1007/s11280-021-00920-4.

[35] C. Greenhow, S. M. Galvin, D. L. Brandon, and E. Askari, “A decade of research on K-12 teaching and teacher learning with social media: Insights on the state of the field,” *Teach. Coll. Rec.*, vol. 122, no. 6, pp. 4–48, 2020, doi: 10.1177/016146812012200602.

[36] S. A. Mirlohi Falavarjani, J. Jovanovic, H. Fani, A. A. Ghorbani, Z. Noorian, and E. Bagheri, “On the causal relation between real world activities and emotional expressions of social media users,” *J. Assoc. Inf. Sci. Technol.*, vol. 72, no. 6, pp. 723–743, 2021, doi: 10.1002/asi.24440.

[37] A. Wibowo, S. C. Chen, U. Wiangin, Y. Ma, and A. Ruangkanjanases, “Customer behavior as an outcome of social media marketing: The role of social media marketing activity and customer experience,” *Sustain.*, vol. 13, no. 1, pp. 1–18, 2021, doi: 10.3390/su13010189.

[38] Aschbrenner, J. A. Naslund, A. Bondre, J. Torous, and K. A., “Naslund.._,” *J. Technol. Behav. Sci.*, vol. 5, no. 3, pp. 245–257, 2020, [Online]. Available: https://doi.org/10.1007/s41347-020-00134-x

[39] T. Hillman, M. Lundin, A. B. Rensfeldt, A. Lantz-Andersson, and L. Peterson, “Moderating professional learning on social media - A balance between monitoring, facilitation and expert membership,” *Comput. Educ.*, vol. 168, no. July 2020, p. 104191, 2021, doi: 10.1016/j.compedu.2021.104191.

[40] “• Social Media Monitoring and Moderation - Google Search.” https://www.google.co.in/search?q=•%09Social+Media+Monitoring+and+Moderation&sca_esv=f65d9110a0398786&udm=2&biw=1517&bih=712&sxsrf=.

[41] M. Srikanth, A. Liu, N. Adams-Cohen, J. Cao, R. M. Alvarez, and A. Anandkumar, “Dynamic Social Media Monitoring for Fast-Evolving Online Discussions,” *Proc. ACM SIGKDD Int. Conf. Knowl. Discov. Data Min.*, pp. 3576–3584, 2021, doi: 10.1145/3447548.3467171.

[42] P. Chauhan, N. Sharma, and G. Sikka, “The emergence of social media data and sentiment analysis in election prediction,” *J. Ambient Intell. Humaniz. Comput.*, vol. 12, no. 2, pp. 2601–2627, 2021, doi: 10.1007/s12652-020-02423-y.

[43] X. Wan and L. Tian, “User Stress Detection Using Social Media Text: A Novel Machine Learning Approach,” *Int. J. Comput. Commun. Control*, vol. 19, no. 5, pp. 1–15, 2024, doi: 10.15837/ijccc.2024.5.6772.

[44] P. K. Rangarjan *et al.*, “The social media sentiment analysis framework: deep learning for sentiment analysis on social media,” *Int. J. Electr. Comput. Eng.*, vol. 14, no. 3, pp. 3394–3405, 2024, doi: 10.11591/ijece.v14i3.pp3394-3405.

[45] A. Alotaibi and F. Nadeem, “Leveraging Social Media and Deep Learning for Sentiment Analysis for Smart Governance: A Case Study of Public Reactions to Educational Reforms in Saudi Arabia,” *Computers*, vol. 13, no. 11, 2024, doi:

10.3390/computers13110280.