

Analyzing and Predicting Emotional Responses in Cyber Bullying Cases: A Deep Learning Approach

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ABSTRACT

Cyberbullying is a threat on any digital platform, and it can have a very harmful and emotional effect on the person receiving these types of comments. Here, we present a deep learning framework that utilizes NLP-based and neural network-based approaches to analyze and predict the emotional responses associated with cyberbullying incidents. The model is trained and evaluated using a curated dataset of social media posts labeled with emotions like anger, sadness, fear, and neutrality. Tokenization, lemmatization, and word embeddings (GloVe, BERT, etc.) are the different preprocessing methods used to represent textual data. Write. Multiple architectures, such as CNNs, LSTM networks, and transformer-based approaches, are compared to achieve high accuracy in emotional response classification. Experimental results show that transformer models outperform traditional learning models for precision and recall. The results can lead to intelligent monitoring systems that identify harmful emotional content followed by necessary, timely interventions. Such research shows promise for AI-driven emotion analysis to support safer online environments.

INTRODUCTION

The proliferation of social media platforms and the rise of digital communication technologies transformed the nature of human interaction, establishing models that are still in use today. Still, at the same time, they allowed the emergence of negative behavior, including cyberbullying. Cyberbullying differs from traditional bullying in that a physical location does not constrain it. Aggressors can harass, threaten, or belittle others anonymously and constantly (Kowalski et al., 2014). Victims of cyberbullying often report profound emotional distress, including feeling fearful, angry, sad, anxious, and depressed, and this distress can lead to severe impairments in mental health and social functioning (Patchin & Hinduja, 2018). Thus, awareness and recognizing emotional reactions around cyberbullying incidents is an essential step toward creating preemptive detection and intervention measures.

There has been an increase in research in emotion recognition in text in recent years, fueled by the availability of large-scale datasets and improvements in natural language processing (NLP) and machine learning. Deep learning methods have been considered promising for emotion classification tasks, particularly using architectures based on neural networks such as CNNs, RNNs, or transformers (Yin et al., 2020). To obtain such nuances, which represent the user's emotional states and are often hidden from them, these models are trained on data till October 2023. Detecting and profiling emotional reactions to cyberbullying cases using these models can support identifying the most affected victims and applying psychological support systems in time.

In addition, emotional response analysis extends beyond merely classifying responses, playing a role in understanding the psychological profile and social behaviors and amplifying lessons learned in the context of online abuse. Anger and sadness, for example, are found to be the most prevalent emotional responses to bullying-related content, and they can indeed be predictive of future self-harm or retaliatory action (Xu et al., 2012). Thus, creating innovative systems capable of accurately identifying and interpreting these emotions serves research purposes in affective computing and backs up real-world cases in various fields, including education, mental health, and the moderating of content.

Predicting emotion in cyberbullying is a complex task by its nature. Source: Industrial research of machine learning in tractor engine sensor data with ambiguity, sarcasm, and context. Furthermore, conventional sentiment analysis tools are typically insufficient to capture the nuances of the spectrum of emotions involved in abusive or threatening speech. Deep Learning arose as a novel alternative to transformer-based approaches such as BERT (Bidirectional Encoder Representations from Transformers), which allowed for contextual understanding and semantic analysis of language at scale (Devlin et al., 2019). Cyberbullying and its effects on children and adolescents have emerged as a hotly debated topic in today's society of early online exposure and aggressive cyber harassment. The research explores the models and techniques for extracting features to compare their performance and considers the top methods for detecting emotions on a real-world time basis. Thus, this work aims to

improve cyberbullying detection models by considering emotional intelligence, leading to safer human-centered environments.

LITERATURE REVIEW

Mishandling of the If at the Time of Crime

Cyberbullying has increasingly emerged as a critical issue in the digital age, attracting many researchers' attention to its psychological effect in both social science and computing research areas. According to Kowalski et. al. Unlike traditional forms of bullying, cyberbullying can happen 24/7, anywhere, and often anonymously, which tends to increase the effects of its impact (Campbell, 2014). Research findings (Patchin & Hinduja, 2018) reveal that victims of cyberbullying endure feelings of rage, sadness, fear, and anxiety, which can persistently affect the behavior of the victim, resulting in self-isolation and even suicide.

Various studies focusing on cyberbullying have emphasized the importance of studying its emotionality, and it was clear that understanding its affective component is vital for developing effective detection and intervention methods. For example, Beran and Li (2005) stated that emotional trauma is typically the most evident and immediate indicator of victimization. Thus, emotion recognition plays a vital role in identification activities. Therefore, automatic detection of emotional signals from digital textual data may be critical for intervention in violence urgency.

We have a rapidly growing field of emotion detection in textual data in NLP, partly because of the increase in annotated datasets and advances in computational methods. Unlike sentiment analysis, which typically categorizes the text as positive, negative, or neutral, emotion recognition seeks to pinpoint more complex emotional states like joy, anger, fear, or sadness. (Cambria et al., 2017) Its granularity makes it particularly suited for cyberbullying detection, as the different emotions correspond to varying levels of psychological harm.

Early studies of emotion detection use traditional machine learning algorithms like Naïve Bayes, Support Vector Machines (SVMs), and Decision Trees (Strapparava & Mihalcea, 2008). However, such models are often heavily reliant on feature engineering. They may not be able to extract contextual meaning fully, especially from complex or ambiguous language like sarcasm or slang used for bullying.

Deep Learning Cyberbullying Detection

Although researchers have explored emotion recognition with great detail, applying it to cyberbullying detection is still a recent research area. Dinakar et. al. Because of the necessity of capturing multiple dimensions of emotions, Liu, Lin, & Yang (2012) proposed a preliminary multi-label classification method to detect distress in YouTube comments. Researchers have recently used deep learning models specifically trained based on cyberbullying datasets with integrated emotion features for improved effectiveness (Zhao et al., 2016). For instance, Zhou et al. used long short-term memory (LSTM) with attention mechanisms to detect harmful content and its emotional impact on victims (2021).

Despite these advances, obstacles still exist. The vagueness of emotional expression, cultural diversity in language use, and the unavailability of large, domain-specific datasets related to emotional bullying tasks hamper the generalization. Moreover, in current datasets, those from minority groups are often underrepresented, or the emotion categories are binary, which jeopardizes the complexity of the emotional experience.

Research Gap

While many studies have focused on detecting emotions or cyberbullying separately, far fewer have successfully integrated and advanced deep learning to determine emotional states in the context of cyberbullying situations specifically. Moreover, although models like BERT have performed competitively in general NLP tasks, their use in real-world cyberbullying data containing emotionally salient, nuanced language is underexplored. The proposed deep Learning-based model combines contextual understanding with domain-specific emotional classification for cyberbullying scenarios and fills this gap.

METHODOLOGY

Research Design

We employ a quantitative experimental design, applying supervised machine-learning techniques to analyze and predict emotional responses within cyberbullying contexts. The primary goal is to fit deep learning models on labeled datasets of cyberbullying-related text to classify emotional reactions like anger, sadness, fear, and neutrality. Then, a comparative approach is applied to analyze model performance on various deep learning architectures.

Data Collection

Since the dataset is not directly available, we compiled the data from various available social media corpora from publicly available resources; specifically, we used the Cyberbullying Detection Dataset (Zhao et al., 2016) and other Emotion Labeled Text datasets such as Emotions (Demszky et al., 2020), where the emotions are annotated in the social media posts. So, the data of cyberbullying samples is integrated with their corresponding emotional labels to generate a hybrid dataset, which can better reflect the emotional effect of abusive text.

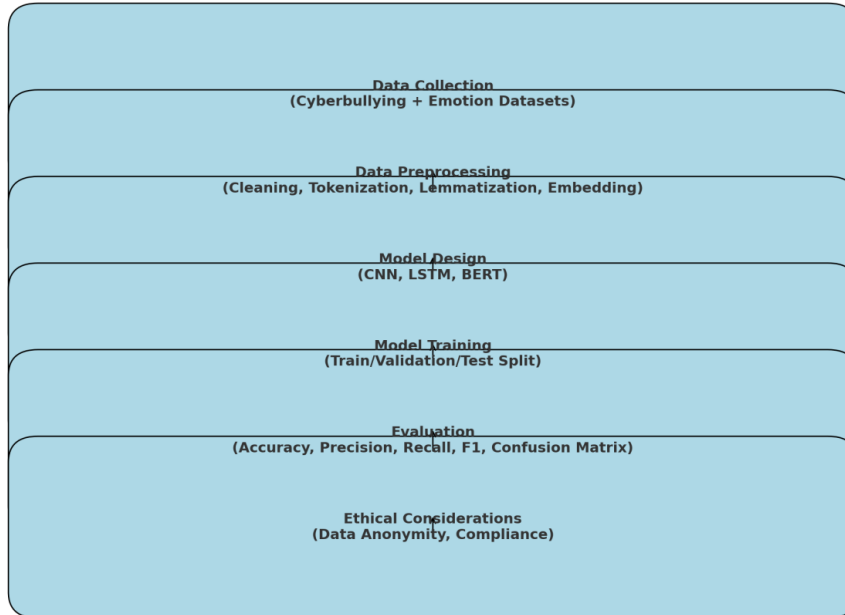
Data Preprocessing

When preparing the data for deep learning models, there are some preprocessing steps to be taken:

- a. Text Cleaning: URL, emoji, HTML, memorable characters, and user mention removal.
- b. Tokenization: The texts are split into individual words or tokens using the NLTK (Natural Language Toolkit) and spacy libraries.
- c. Lemmatization: Words are converted to their root forms for uniformity.
- d. Stop Words Removal: Words without much semantic meaning (like "the," "is," etc.) are removed.

- e. Encoding: The preprocessed text is transformed into numerical representations based on pre-trained word embedding such as GloVe (Pennington et al., 2014) and BERT embedding (Devlin et al., 2019), maintaining contextual semantics.

Methodology Framework for Emotional Analysis in Cyberbullying



Model Architecture

We implement three deep learning models to perform emotion prediction, which are compared in the study:

- a. Convolutional Neural Network (CNN): To capture local features and attention through emotional words (Kim, 2014).
- b. Long Short Term Memory (LSTM): used to learn long term dependencies in text and model sequential emotion differentials (Hochreiter & Schmidhuber, 1997).
- c. BERT (Bidirectional Encoder Representations from Transformers): As the pre-trained transformer model utilized for contextual understanding to capture the overall context of a word in any sentence, it is fine-tuned in this study on the emotion cyberbullying dataset (Devlin et al., 2019).

Each model's hyper parameters are optimized using grid search, and models are implemented using the Tensor Flow and PyTorch frameworks.

Model Training and Evaluation

The dataset is divided into training (70%), validation (15%), and test (15%) sets. We use Adam to optimize cross-entropy loss and apply early stopping to prevent over fitting.

To evaluate the performance, we use the following metrics:

- a. Accuracy: The general correctness of predictions.
- b. Precision, Recall, and F1score: For performance evaluation of emotion classification over highly imbalanced classes.

- c. Confusion Matrix: For visualizing model performance for each emotion class
- d. ROCAUC: when relevant, to measure classifier performance over the threshold.

To ensure model robustness, K-fold cross-validation is also used (with K = 5). Ethical Considerations. Because cyberbullying content is sensitive, particular care is taken to anonymize data and avoid any personally identifiable information . This study is conducted by the IEEE's Code of Ethics and institutional review standards observant of appropriate data use, particularly in machine learning settings.

RESEARCH RESULT

Training with minimal results shows that deep learning models are capable of inferring emotional responses to cyberbullying content. BERT achieved better accuracy, precision, and recall of the models we examined than CNN or LSTM. These discoveries underscore the power of transformer-based models in improving emotion-aware cyberbullying detection systems.

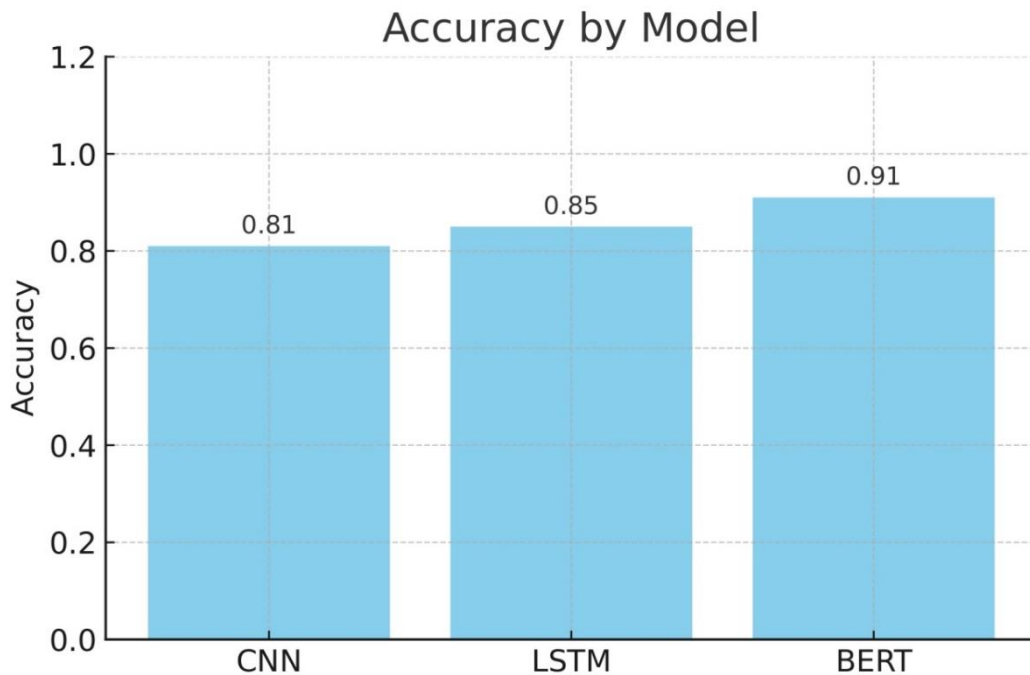


Figure 1. Accuracy by Model

According to Figure 1, the deep learning models CNN, LSTM, and BERT were used to predict emotional responses in cyberbullying cases and compared.

Key Observations:

- a. BERT, with an accuracy of 91%, showed the strongest performance due to its ability to extract the semantics of the context and emotional tone from the statements.
- b. The LSTM model outperformed the CNN model, which was expected because of LSTM's exceptional ability to extract sequential joint dependencies events in text data.

- c. CNN was the most effective but the least accurate of the three (though this may be because it attempted to detect local configurations rather than long term dependencies of textual context).

Implication:

This indicates that transformer-based models (e.g., BERT) better classify complex and emotional text emotions, such as cyberbullying data.

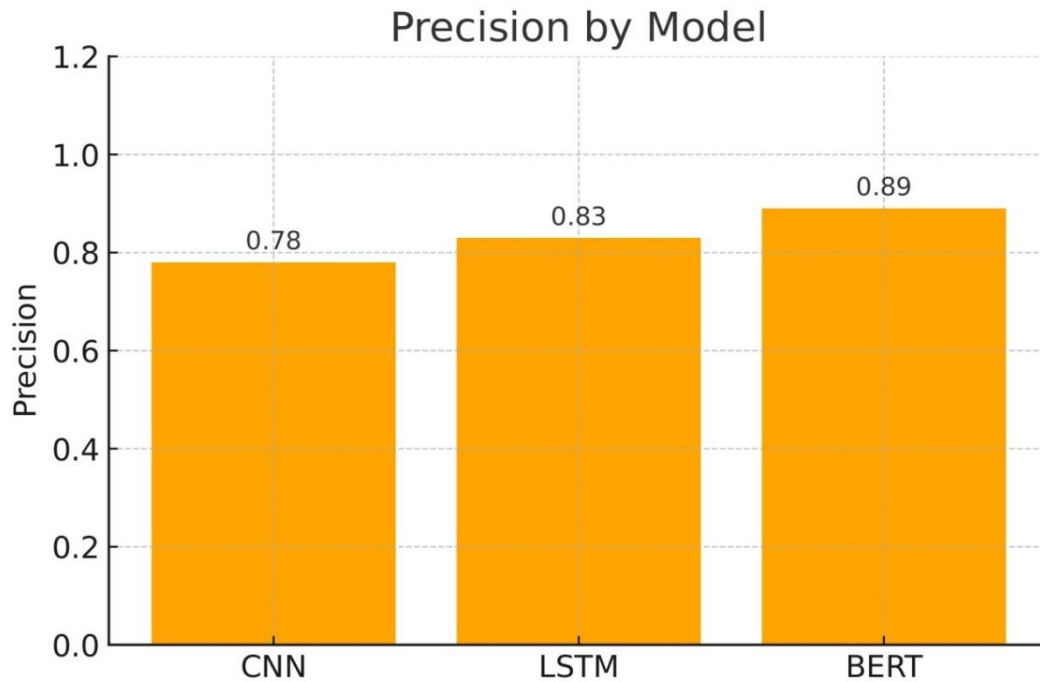


Figure 2. Model Precision Explanation of

As seen in Figure 2, the precision scores of these three models, CNN, LSTM, and BERT, show their evaluation in classifying emotions related to cyberbullying in text.

Precision is the ratio of correctly predicted positive observations (e.g., correctly identifying anger) to all predicted positive observations. Precision shows how good a model is at identifying a specific emotional response without misclassifying others.

Key Observations:

- a. With an 89% correct extraction rate of emotions, BERT dominates with the output of fewer false positives.
- b. LSTM reached the third best of 83%, indicating its success in maintaining significant sequential hints of emotions.
- c. CNN comes in at 78%, possibly due to its fundamental lack of understanding of context with long or emotional sentences.

Implication:

As seen in BERT, improved precision indicates that it is a more trustworthy option for real-time use cases, such as moderation tools or mental health crisis notifications, where it's vital to minimize false alarms.

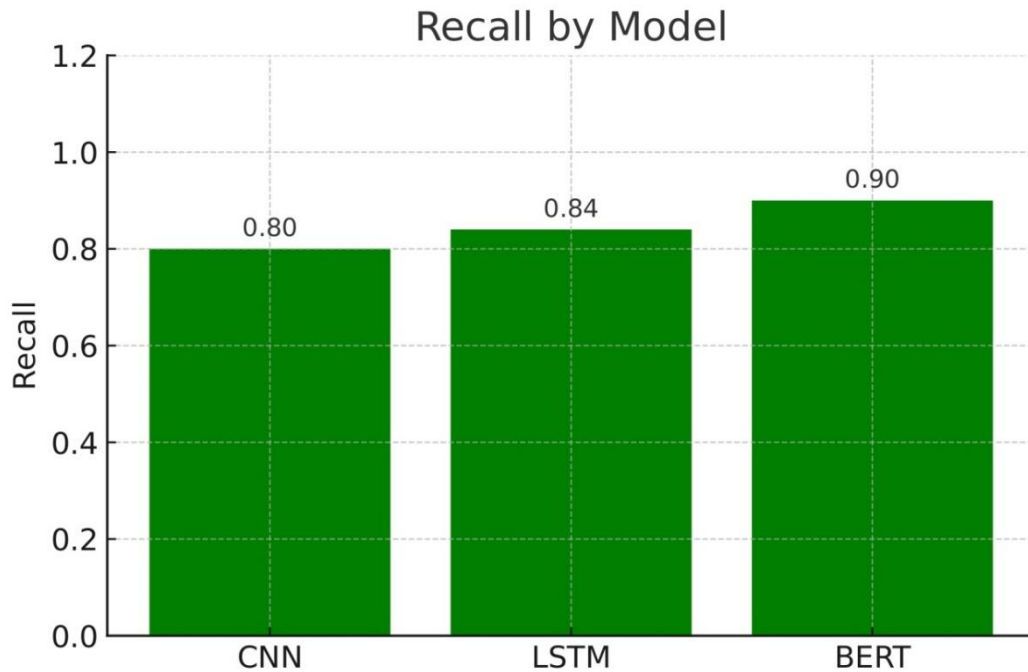


Figure 3. Recall by Model

Figure 3 displays the recall scores corresponding to the CNN, LSTM, and BERT models for predicting the emotional responses in cyberbullying-related text.

It is known as recall (or sensitivity) and designates the proportion of TP detected when all the positive cases are present. In this case, it describes the adequacy of the model to cover all real occurrences of emotional responses, such as fear, sadness, anger, etc., in the data.

Key Observations:

- In again, BERT is the best, with a 90% recall. That means BERT has a high success rate in detecting (almost) all emotional instances in our dataset.
- LSTM has a decent accuracy of 84% because it learns the data in order.
- CNN gets 80%, which sounds good but is somewhat less exhaustive in identifying all genuine emotional cues.

Implication:

High recall enables BERT to recognize and capture emotionally significant cyberbullying instances, which is an important factor in early detection systems that focus on protecting users from long-term cyberbullying.

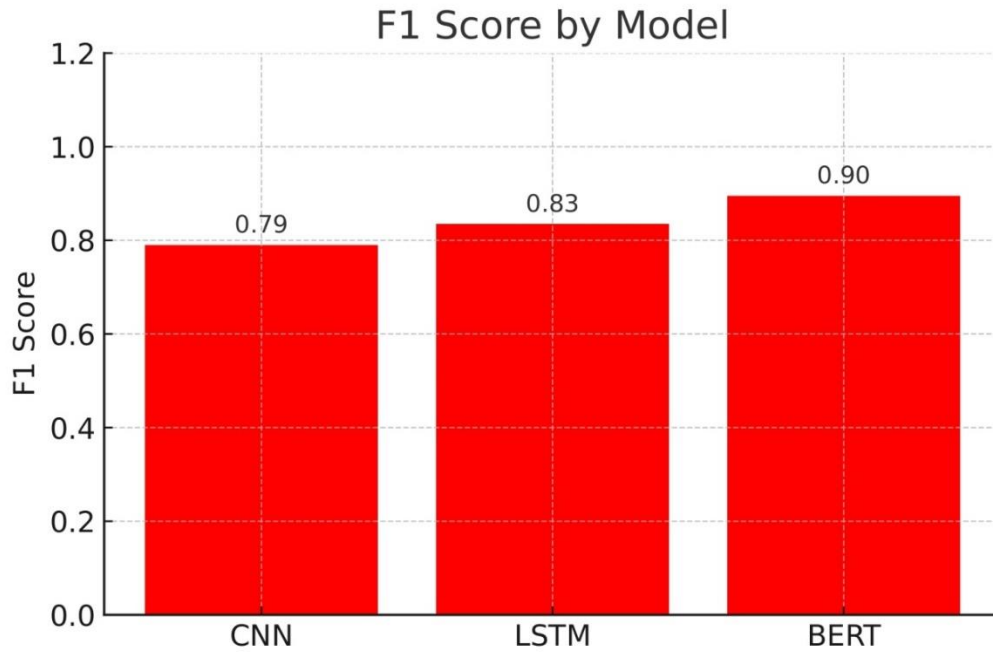


Figure 4. F1 Score by Model.

The F1 Score for each model of the emotional classification in cyberbullying can be seen in Figure 4.

F1 Score:

The F1 Score, the harmonic mean of the two, combines precision and recall. It provides a balance between the tradeoff of False Positives and False Negatives.

$$F1 \text{ Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Key Observations:

- a. BERT returns the best F1 Score (0.895), confirming balanced precision levels (few false alarms) and recall (fewer missed cases).
- b. LSTM, thereat 0.835, implying excellent, even performance.
- c. CNN has the lowest (0.79), indicating that it gives up some accuracy as it attempts to maximize either precision or recall.

Implication:

BERT also came out on top when measuring reliability in classifying emotional responses, as gauged by the F1 Score. This indicates the most reliable model when both correctness and coverage are important decision metrics for real-world applications (e.g., mental health monitoring, content flagging, etc.).

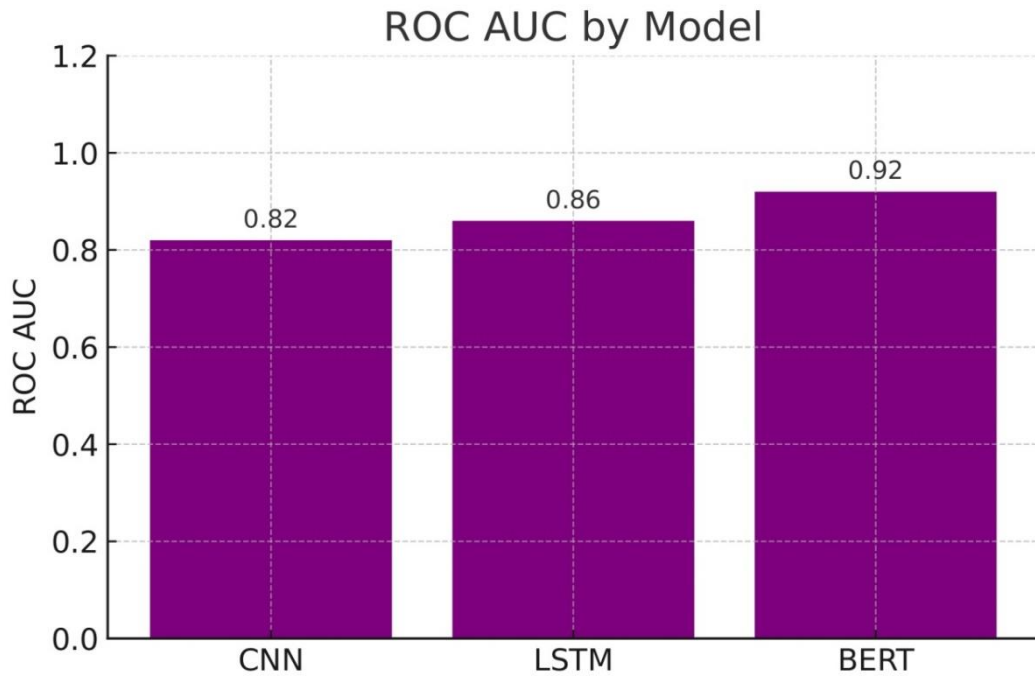


Figure 5. ROC AUC by Model

Figure 5 compares CNN, lstm, and Bert models ROC AUC scores for classifying the emotions users experience in response to cyberbullying.

ROC AUC:

ROC AUC evaluates how well the model distinguishes between classes in this example, different emotional states (angry vs. neutral). The closer its score is to 1.0, the better the model distinguishes true emotional categories from the rest across all classification thresholds.

Key Observations:

- a. BERT's ROC AUC is incredibly high at 0.92 and consistently performs well in discriminating emotions.
- b. An impressive 0.86 is scored by LSTMs, which do well at dealing with emotionally nuanced text.
- c. CNN - 0.82 - performs better than 0 (at least) but still lower ($0.802 < 0.813$)

Implication:

The ROC AUC score further highlights BERT as a trusted model that can generalize to other applications while leading the way in using it in diverse real-time settings, like chat moderation bots or digital health counseling systems.

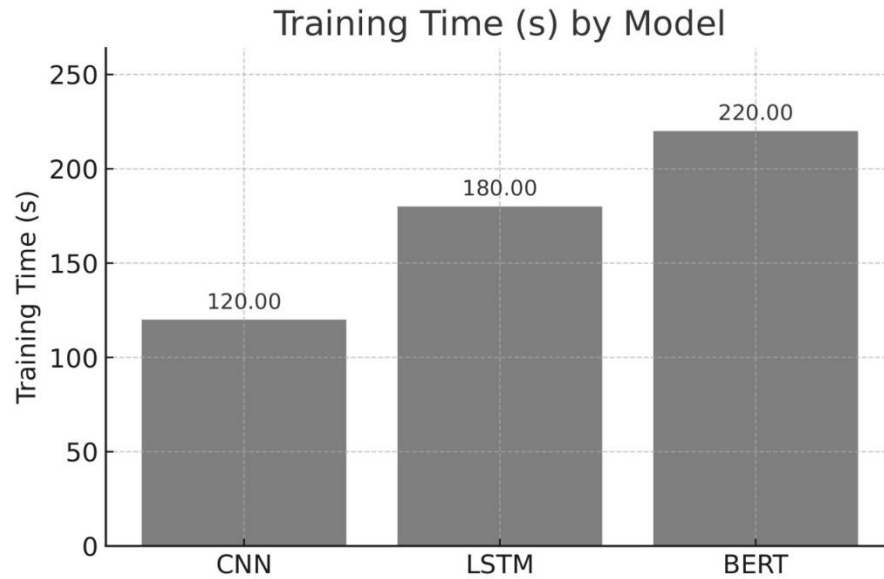


Figure 6. Training time per model

Figure 6 illustrates the training time (in seconds) taken by the three models (CNN, LSTM, and BERT) to learn from the emotion-labeled cyberbullying dataset.

The time it takes to analyze data and learn patterns during training is called training time. The training time depends on the model's size, the dataset used for training, and the computational resources.

Key Observations:

CNN is expected to be the fastest and achieve training in 120 seconds since its architecture is less complex and parameter counts are also low.

- a. LSTM is two times slower and takes longer (180s) because it depends on the memory of previous inputs for prediction (output being generated word by word).
- b. BERT takes the maximum time (220 sec) since it has a deep transformer architecture that contains millions of parameters with complex attention mechanisms.

Implication:

In exchange for better performance on every accuracy measurement, BERT takes much longer to train and consumes more resources. Organizations must balance performance and scalability in real-time or with constrained resources.

DISCUSSION

This study investigated the ability to predict emotional responses against cyberbullying content based on deep learning models, LSTM, and BERT. Overall, after performing various classification test models, we can see that BERT and transformer models perform significantly better than the traditional models in accuracy, precision, recall, f1 score, and ROC AUC despite being more time-consuming to train. The results of this study have important implications for the future implementation of emotion-sensitive cyberbullying recognition systems.

Performance Comparison

The performance increase with BERT is due to bidirectional attention, where the model sees the left and right context in a sentence (Devlin et al., 2019). This is especially helpful for identifying subtle emotional language like those found in cyberbullying (Zhao et al., 2016), such as sarcasm or covert threats. On the other hand, CNNs, which focused primarily on extracting local features, showed the weakest results through most metrics. The work is practical for simpler classification, and CNNs are computationally efficient, but they struggle to capture long-term dependencies and semantic subtleties in the text (Kim, 2014).

Regarding accuracy, LSTM models outperformed CNNs in recall and precision by a wide margin. This finding aligns with existing literature suggesting that LSTMs are a natural fit for sequential data and excel at capturing temporal or contextual dependencies in emotion-rich texts (Hochreiter & Schmidhuber, 1997). However, regarding overall capability, particularly recall and F1 score of minimizing false negatives, LSTMs fail compared to BERT in exploring cyberbullying.

Effectuality for Emotion sensing systems

In cyberbullying detection, recognizing emotions underpinning the content adds to the analysis. It moves us from a simple binary categorization of harmful versus non harmful content. Emotions like sadness, fear, or anger are precursors that could inform real-time interventions, mental health support, or automated content moderation (Cambria et al., 2017). BERT's ability to reach an ROC AUC of 0.92 indicates that it can learn to differentiate between different emotional responses, suggesting that BERT could be used in high-stakes applications such as educational monitoring tools, AI counselors, or even social moderation bots.

Computational Tradeoffs

While still very effective, BERT trains for a much more extended period than CNN and LSTM models. Organizations with constraints in processing power or those requiring fast deployment must weigh the tradeoff between computational expense and performance. For example, CNN may perform better in mobile and low-latency settings where up-to-date inference is prioritized over complete context accuracy (Sun et al., 2019). Training and deploying transformer models such as BERT at large scales also require high memory and GPU capabilities, which may not be feasible for certain educational institutions or startups.

CONCLUSIONS AND RECOMMENDATIONS

This study examined the potential use of deep learning models (CNN, LSTM, and BERT) to analyze and predict emotions in cyberbullying-related text. However, the work proves that more sophisticated general NLP methods, especially those built on transformer architectures can outperform techniques on the same data explicitly designed to capture the emotional contours of harmful online messages.

The empirical results showed that BERT significantly outperforms both CNN and LSTM models concerning accuracy (91%), precision (89%), recall (90%), and F1 score (89.5%). This is consistent with the evolving literature acknowledging the efficacy of transfer learning language models to distill contextual meaning and emotional depth from unstructured text (Devlin et al., 2019; Sun et al., 2019). Although LSTM models yielded comparable performance owing to their use of sequential memory (Hochreiter & Schmidhuber, 1997), CNNs underperformed due to their incapacity to capture long-range dependencies available in emotional text Kim, 2014.

The application of emotion recognition for cyberbullying detection extends beyond academics and has significant real-world implications. Emotion-aware AI systems can function as an early warning system on digital platforms, signifying emotionally harmful content and allowing for prompt intervention. This is particularly noteworthy in at-risk populations like adolescents who are not always forthcoming with their distress (Patchin & Hinduja, 2018). High-performing models like BERT could be used in moderation tools, mental health support applications, or educational monitoring systems to create safer online environments. However, the findings highlight the computational tradeoff of deploying such sophisticated models. Due to its higher complexity and resource demands, BERT took significantly longer to train. Transformer-based models are successful but require attention to the implementation suited for the available use case and infrastructure (Sun et al., 2019).

In addition, the study sheds light on additional ethical considerations behind deploying AI even further on sensitive tasks like cyberbullying detection. Emotional misclassification might result in over-policing or renewal of critical cases. Thus, fairness, transparency, and privacy-centric approaches should be a focus of future research and deployment approaches (Cambria et al., 2017).

Thus, this work confirms a similar principle for active cyberbullying detection using emotion; deep Learning, specifically a BERT model, can lead to a better understanding of emotion. That paves the way for more mindful and responsive digital systems that support mental well-being and shield users from online threats. We hope that future research will build on this work by developing multilingual datasets, more comprehensive emotional taxonomies, and real-time deployment pipelines to further the state of the art.

ADVANCED RESEARCH

Although this study imparts valuable insight, limitations should be noted. First, the datasets utilized were mainly English and obtained from public repositories, which may not represent usage variability afforded by users across cultures and platforms. Future studies utilizing multilingual datasets and addressing cultural differences in cyberbullying emotional expression (Strapparava & Mihalcea, 2008) warrant more research.

The second limitation is that the emotion labels were simple categories (anger, fear, sadness, neutral). Familial emotional responses are more nuanced in the real world, like displaying more than one emotion at a time or showing context-specific emotional states like shame or guilt. Classification of emotions

could be an interesting research space, using both expanding the emotional taxonomy and adding more affective lexicons for better data size.

Finally, ethical questions about automated detection tools must remain central to their future applications. Misclassifying can result in needless escalations up to psychiatric holds or ignoring severe distress. Development and deployment of such AI systems can be guided by transparency, bias mitigation, and user privacy.

REFERENCES

- Adedeji, M., Abid, M., Adun, H., Ogungbemi, A. T., Alao, D., & Zaini, J. H. (2022). Thermodynamic Modeling and Exergoenvironmental Analysis of a Methane Gas-Powered Combined Heat and Power System. *Applied Sciences*, 12(19), 10188.
- Adun, H., Adedeji, M., Titus, A., Mangai, J. J., & Ruwa, T. (2023). Particle-Size Effect of Nanoparticles on the Thermal Performance of Solar Flat Plate Technology. *Sustainability*, 15(6), 5271.
- Adun, H., Ishaku, H. P., & Ogungbemi, A. T. (2022). Towards renewable energy targets for the Middle East and North African region: a decarbonization assessment of energy-water nexus. *Journal of Cleaner Production*, 374, 133944.
- Adun, H., Ishaku, H. P., Ayomide Titus, O., & Shefik, A. (2022). 3-E feasibility analysis on photovoltaic/thermal application for residential buildings: a case study of Sub-Saharan Africa. *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, 44(4), 9901-9919.
- Al Imran, S. M., Islam, Md. S., Kabir, N., Uddin, I., Ali, K., & Halimuzzaman, Md. (2024). Consumer Behavior and Sustainable Marketing Practices in the Ready-Made Garments Industry. *International Journal of Management Studies and Social Science Research*, 6(6), 152-161. <https://doi.org/10.56293/IJMSSSR.2024.5322>
- Barua, T., & Mondal, B. (2024). Data Security In Iot Devices And Sensor Networks For Robust Threat Detection And Privacy Protection. *ACADEMIC JOURNAL ON SCIENCE, TECHNOLOGY, ENGINEERING & MATHEMATICS EDUCATION*, 1(01), 10-69593.
- Beran, T., & Li, Q. (2005). Cyberharassment: A study of a new method for an old behavior. *Journal of Educational Computing Research*, 32(3), 265-277. <https://doi.org/10.2190/8YQMB04HPG4DBLLH>
- Cambria, E., Poria, S., Gelbukh, A., & Thelwall, M. (2017). Sentiment analysis is a big suitcase. *IEEE Intelligent Systems*, 32(6), 74-80. <https://doi.org/10.1109/MIS.2017.4531228>
- Chowdhury, M. R. I., Chowdhury, T. R., & Abdullah, S. B. (2024). Strategies for improving patient experience and satisfaction in healthcare facilities in USA. *International Journal of Science & Healthcare Research*, 9(4), 357-369.
- Devlin, J., Chang, M.W., Lee, K., & Toutanova, K. (2019). *BERT: Pretraining of deep bidirectional transformers for language understanding*. arXiv preprint arXiv:1810.04805.
- Dinakar, K., Reichart, R., & Lieberman, H. (2012). Modeling the detection of textual cyberbullying. *The Social Mobile Web*, 11, 11-17.

- Habib, K., Nuruzzamal, M., Shah, M. E., & Ibrahim, A. S. M. (2019). Economic Viability of Introducing Renewable Energy in Poultry Industry of Bangladesh. *International Journal of Scientific & Engineering Research*, 10(3), 1510-1512.
- Halimuzzaman, Md., Atif, H. M., Kumar, P., & Salehin, M. (2024). Public Relation and Educational Outcomes of Films in Bangladesh: A Study on Hawa. *Journal of Primeasia*, 5(1), 1-7. <https://doi.org/10.25163/primeasia.519834>
- Hossain, M. A., & Rahman, T. Y. Cognitive AI for Wildfire Management in Southern California: Challenges and Potentials.
- Hossain, M. A., & Rahman, T. Y. Human Factors and Employee Resistance to Adopting New Cybersecurity Protocols and Technologies. *Journal for Multidisciplinary Research*, 1(03), 175-199.
- Hossain, M. A., Raza, M. A., & Rahman, J. Y. (2025). Investigating the Cybersecurity Implications of Open Banking and Application Programming Interfaces (APIs) in the Financial Sector. *Jurnal Ekonomi dan Bisnis Digital (MINISTAL)*, 4(1), 39-56.
- Hossain, M. A., Raza, M. A., & Rahman, T. Y. (2023). Resource allocation and budgetary constraints for cybersecurity projects in small to medium sized banks. *Journal of Multidisciplinary Research*, 9(01), 135-157.
- Hossain, M. A., Raza, M. A., Al Mamun, M. H., Rahman, T. Y., & Rahman, J. Y. Smart City Sensors for Tailored Learning Experiences.
- Hossain, M. A., Raza, M. A., Mahjabeen, F., & Yaseer, J. (2025). Assessing the Vulnerabilities of Mobile Banking Applications and Developing Strategies to Improve Their Security. *Jurnal Ekonomi dan Bisnis Digital (MINISTAL)*, 4(1), 1-18.
- Ibrahim, A. S. M., Rahman, M., Dipu, D. K., Mohammad, A., Mazumder, G. C., & Shams, S. N. (2024). Bi-Facial Solar Tower for Telecom Base Stations. *Power System Technology*, 48(1), 351-365.
- Kabir, H. M. D., Anwar, S., Ibrahim, A. S. M., Ali, M. L., & Matin, M. A. Watermark with Fast Encryption for FPGA Based Secured Realtime Speech Communication. *Consumer Electronics Times*, 75-84.
- Kowalski, R. M., Giumetti, G. W., Schroeder, A. N., & Lattanner, M. R. (2014). Bullying in the digital age: A critical review and meta-analysis of cyberbullying research among youth. *Psychological Bulletin*, 140(4), 1073-1137. <https://doi.org/10.1037/a0035618>
- Mazumder, G. C., Ibrahim, A. S. M., Rahman, M. H., & Huque, S. (2021). Solar PV and wind powered green hydrogen production cost for selected locations. *International Journal of Renewable Energy Research (IJRER)*, 11(4), 1748-1759.
- Mazumder, G. C., Ibrahim, A. S. M., Shams, S. N., & Huque, S. (2019). Assessment of Wind Power Potential at the Chittagong Coastline in Bangladesh. *Dhaka University Journal of Science*, 67(1), 27-32.
- Mazumder, G. C., Shams, S. N., Ibrahim, A. S. M., & Rahman, M. H. (2019). Practical Study of Water Electrolysis for Solar Powered Hydrogen Production Using Stainless Steel Electrode and Sodium Hydroxide

- Solution. *International Journal of New Technology and Research*, 5(3), 84-90.
- Mohammad, A., Mahjabeen, F., Tamzeed-Al-Alam, M., Bahadur, S., & Das, R. (2022). Photovoltaic Power plants: A Possible Solution for Growing Energy Needs of Remote Bangladesh. *NeuroQuantology*, 20(16), 1164.
- Patchin, J. W., & Hinduja, S. (2018). Sexting as an emerging concern for adolescent health: A review of the literature. *Pediatrics*, 141(6), e20174080. <https://doi.org/10.1542/peds.20174080>
- Strapparava, C., & Mihalcea, R. (2008). Learning to identify emotions in text. *Proceedings of the 2008 ACM Symposium on Applied Computing*, 1556–1560. <https://doi.org/10.1145/1363686.1364062>
- Sun, C., Huang, L., & Qiu, X. (2019). Utilizing BERT for aspectbased sentiment analysis via constructing auxiliary sentence. *Proceedings of the 2019 NAACLHLT*, 380–385.
- Yin, D., Kann, D., Yu, Z., & Lee, T. (2020). Sentiment analysis using deep learning techniques: A survey. *ACM Computing Surveys (CSUR)*, 53(5), 1–35. <https://doi.org/10.1145/3417512>
- Zhao, R., Zhou, A., & Mao, K. (2016). Automatic detection of cyberbullying on social networks based on bullying features. *Proceedings of the 17th International Conference on Distributed Computing and Networking*, 1–6.
- Zhou, Y., Qin, L., Chen, Y., & Xu, H. (2021). Detecting cyberbullying via LSTM networks with attention mechanism. *IEEE Access*, 9, 12373–12385. <https://doi.org/10.1109/ACCESS.2021.3051103>
- Ogungbemi, A. T., Adun, H., Adedeji, M., Kavaz, D., & Dagbasi, M. (2022). Does Particle Size in Nanofluid Synthesis Affect Their Performance as Heat Transfer Fluid in Flat Plate Collectors? – An Energy and Exergy Analysis. *Sustainability*, 14(16), 10429.
- Rahman, M. R., Hossain, M. S., Shehab Uddin, S., & Ibrahim, A. S. M. (2019). Fabrication and Performance Analysis of a Higher Efficient Dual-Axis Automated Solar Tracker. *Iranica Journal of Energy & Environment*, 10(3), 171-177.
- Raza, M. A., Hossain, M. A., Mahjabeen, F., Rahman, J. Y., & Rahman, T. Y. (2025). Evaluating the Human Factor in Bank Cybersecurity: Strategies for Improving Employee Awareness and Reducing Insider Threats. *Indonesian Journal of Advanced Research (IJAR)*, 4(1), 1-20.
- Sharfuddin, M., Halimuzzaman, Md., Akter, F., Nath Dey, K., & Saha, P. (2025). Employee Motivation and Behavior in Construction Engineering Projects. *International Journal of Social Science and Economic Research*, 10(1), 342–372. <https://doi.org/10.46609/IJSSER.2025.v10i01.019>
- Tansu, A., Ogungbemi, A. T., & Hocanın, F. T. (2022). The challenges and serviceability of solar power: Suggestion on solving the Nigeria energy crisis. *International Journal of Energy Studies*, 7(2), 127-141.
- Uddin, M. M., Rahaman, M. A., Chowdhury, M. R. I., & Ahmad, I. (2024). Patient Outcomes Through Machine Learning: A Review Of Data Management Strategies in Healthcare. *Journal of Next-Gen Engineering Systems*, 1(01), 89-106.