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Aspect-Based Hybrid CNN With BERT Embeddings For Fine-Grained And Explainable Emotion Recognition

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Abstract: Background / Context: The rapid growth of IoT devices in smart city environments generated massive streams of real-time data, creating strong demand for efficient and secure anomaly detection mechanisms. In that vein, centrally administered AI methods are plagued by bandwidth limitations, latency, and privacy concerns, especially for large-scale deployments. This motivated the shift toward decentralized edge intelligence and federated learning for on-device analytics.Problem/Gap: Most of the anomaly detection frameworks used so far relied on cloud-centric architectures that could not cope with the demanding requirements imposed for real-time responses and did not give sufficient security to sensitive IoT data. Aim/Objective: The paper focuses on the design and evaluation of a federated learning-based edge intelligence framework that is able to conduct IoT anomaly detection tasks over smart city networks in real time. Methodology/Approach: The proposed framework combines Federated Averaging with adaptive edge-side aggregation to enable training of a distributed model without the sharing of raw sensor data. Experiments were conducted on the Edge-IIoTset dataset in an emulated edge computing environment using TensorFlow Federated with MQTT-based communication. Performance was compared against centralized machine learning and cloud-only approaches in different network and workload scenarios. The framework also used various communication optimization techniques to reduce synchronization overhead.Results / Findings: It improved the performance in anomaly detection by up to about 15% compared to the baseline, while comparatively reducing latency and communication costs since it allows for real-time, stable detection across the edge nodes. The system still maintained effective model convergence even with fluctuating network conditions. Implications / Significance: These results demonstrated that the proposed federated edge-based framework can bring scalability with the preservation of privacy and assurance of real-time analytics for IoT infrastructure in smart cities. Such a system will have a great impact on urban safety, predictive maintenance, and resilience of critical city services. Furthermore, this work also provided a practical basis for future deployments of autonomous distributed AI in smart environments.

Keywords: *Federated Learning; Edge Intelligence; IoT; Smart Cities; Anomaly Detection; Real-Time Systems; Privacy Preservation; Distributed Machine Learning.*

1. Introduction

Emotion recognition has become one of the key tasks in natural language processing, driven by its ever-growing importance for a wide range of applications: digital mental health assessment, customer experience monitoring, personalized recommendation systems, social-media behavior analysis, and human-computer interaction(Alyoubi & Sharma, 2023). With more and more human communication happening in online forums, understanding emotional expressions in text is becoming increasingly important for the development of responsive and empathetic AI(Pourrostami et al., 2020). Early approaches typically formulated emotion recognition as a coarse-grained classification problem that predicts a single dominant emotion for an entire sentence or document(Goud & Garg, 2023). This gives a general view of the emotional tone but misses much of the fine-grained emotional landscape that is common in natural language(Chutia & Baruah, 2024).

Human communication is essentially aspect-centric: a single sentence may refer to multiple entities, each with different emotional connotations(Nandwani & Verma, 2021). Consider the following sentence: "The quality of the camera is fantastic, while that of the battery life is disappointing." Traditional sentence-level classifiers overlook such distinctions and tend to yield a single blended emotional label not indicative of what the user actually wanted to convey(Zhang et al., 2022). This has motivated research into Aspect-Based Emotion Recognition-one of the finer-grained versions of Aspect-Based Sentiment Analysis(Wankhade et al., 2022). While the latter is generally focused on polarity-Positive, Negative, and Neutral-ABER explicitly identifies not only the relevant aspects but the respective emotions for each aspect, hence providing a more informed interpretation of the emotions(Hua et al., 2024).

The advancement of transformer-based architectures has significantly improved contextual understanding, especially for emotion classification(De Bruyne et al., 2022a). BERT very effectively captures semantic relationships, contextual cues, and word dependencies; hence, it forms a very solid ground for emotion analysis(Tran et al., 2022). However, even BERT still has difficulties identifying fine-grained emotional triggers, expressed especially in short, localized patterns such as negations, slang expressions, colloquial intensifiers, and idioms common in social-media text(Sundararajan et al., 2017). These cues are often crucial for the correct association of emotions with aspects(Abas et al., 2022). On the other hand, CNNs are very good at detecting local patterns by applying filters over small windows of text, capturing strong n-gram emotional signals(Devlin et al., 2019). However, CNNs have weak global contextual awareness, thus limiting their interpretive capabilities considering aspect-dependent meaning(Chen et al., 2024).

These complementary strengths motivate a hybrid approach. This paper proposes a unified hybrid BERT + CNN architecture to recognize fine-grained, aspect-level emotion by overcoming the limitations of using either BERT or CNN solely(Abdullah & Ahmet, 2023). In this framework, while BERT learns deep contextual embeddings modeling long-range dependencies and semantic relationships, CNN layers catch short-span, high-impact emotional cues(Singh et al., 2024). Further, an attention-based fusion mechanism fuses these global and local representations, hence aligning each aspect to the most relevant emotional phrases within the sentence(Chaudhary et al., 2025). This design especially works effectively in the scenarios of multiple aspects and emotions commonly found in social-media content created by users(Perikos & Diamantopoulos, 2024).

Explanation, besides predictive accuracy, is at the core of most modern AI applications, especially those tasked with human-centered decision-making, such as screening for mental health, assessment of customer sentiment, and behavior analysis(Shalini et al., 2025). More precisely, how a model has reached the prediction of a particular emotion serves as the basis for building trust and transparency, eventually leading to responsible deployment(Karthick, 2025). Along this line, the proposed framework was designed with interpretable mechanisms such as token-level attention visualization and CNN-based Grad-CAM heatmaps to clearly establish which specific words and phrases influenced each aspect-emotion prediction(Selvaraju et al., 2017). This would now help provide more clarity on the reasoning process involved within the model to both the researcher and the end user(Padi et al., 2022).

In general, this research contributes to the literature by filling various gaps in the aspect-level emotion recognition task as an end-to-end system. A proposed hybrid architecture will combine contextual richness, local feature extraction, attention-driven alignment, and multi-

task learning with explainability, likely yielding a robust, accurate, and interpretable approach toward fine-grained emotion understanding. Thus, from a methodological and practical point of view, it provides an opening toward more reliable and transparent emotion-aware NLP systems. Objectives are,

1. To automatically extract aspect terms and opinion-bearing phrases using a multi-task BERT–CNN–CRF architecture for fine-grained identification of emotionally relevant entities.
2. To classify the specific emotion associated with each extracted aspect by leveraging contextual embeddings and attention-driven aspect–context fusion.
3. To estimate emotion intensity on a continuous or scaled range using a regression-based prediction module.
4. To generate interpretable explanations for aspect-level predictions through attention heatmaps and Grad-CAM visualizations.
5. To compare the proposed hybrid model with transformer-only, CNN-only, and attention-based baselines to demonstrate improvements in accuracy, interpretability, and multi-task learning performance.

Novelty

- This hybrid architecture unites the strengths of BERT contextualization and CNNs, especially for local feature extraction in an aspect-level emotion recognition task.
- A multilevel explainable AI mechanism that would use transformer-based attention mechanisms with CNN-based Grad-CAM visualizations for deeper interpretation.
- Unified multi-task learning framework dealing with the tasks of aspect extraction, emotion classification, and intensity prediction jointly.
- Novel attention-based aspect–context interaction module that precisely aligns aspects and emotion-bearing tokens.

Scientific Contributions

- It illustrates that contextual and local feature combinations improve emotional granularity and reduce the misclassification rate.
- It provides a reproducible architecture that is validated across several emotion datasets.
- Demonstrates how joint learning improves consistency between aspect extraction and emotion classification.
- Introduces high-quality interpretability visualizations that enhance trust and transparency.

2. Literature Review

2.1 Transformer-Based Emotion Models

Indeed, context-aware semantics captured by the family of BERT, RoBERTa, DistilBERT, and ALBERT have significantly improved emotion recognition(Hu et al., 2024). However, transformer-based models distribute attention broadly and hence dilute focus on aspect-specific cues. As captured in the literature, there is a difficulty in capturing those short but emotion-bearing expressions such as intensifiers (“very sad”), negations (“not happy”), and idiomatic expressions.

2.2 CNN-Based Hybrids

It works particularly well in sentiment and emotion recognition, especially for local patterns in short texts. Kim's CNN and its derivatives outperform transformers in capturing n-gram dependencies and affective cues. However, these CNNs are not globally contextualized and thus cannot work alone in multi-aspect tasks.

2.3 Fine-Grained Emotion Analysis

While most of the works focuses on ABSA, which is polarity-based, only a few works attend to ABER, which is emotion-based(Y. Liu et al., 2019). Carrying out these three tasks-aspect extraction, emotion identification, and intensity estimation-together in one framework has been done by very few studies. In fact, the prediction of the above tasks as separate components results in their inconsistency(Talaat, 2023).

Most works treat attention as explanation, which, according to recent studies, does not always reflect reasoning. Combining saliency-based methods such as Grad-CAM with attention will improve explainability. So far, however, ABER still lacks any integrated explainable models, and this gap needs to be filled, which is just what this study will do.

3. Methodology

It uses an Aspect-Based Hybrid CNN with BERT Embeddings to accomplish fine-grained, explainable emotion recognition based on open-access comments of Adidas' Instagram posts, where each comment includes:

- Aspect terms
- Emotion annotation
- Valence–Arousal intensity scores

The three tasks that this model performs, therefore, are aspect extraction, aspect-emotion classification, and emotion intensity regression, respectively, followed by generating explainability.

3.1 Data Description

It consists of user comments for branded Instagram posts, annotated for aspect terms, corresponding emotion labels, and valence-arousal intensity values. Each comment contains one or more aspect spans associated with specific emotion categories; these can be mapped into standard classes such as joy, anger, sadness, fear, disgust, and surprise. This dataset contains real social-media language, therefore slang, emojis, abbreviations, and even multi-aspect sentences are included, which makes it suitable for fine-grained aspect-emotion modeling. Data is provided in structured JSON/CSV format, including but not limited to the following fields: text, aspect positions, emotion labels, intensity scores, and optionally image/post metadata. Dataset preparation involves cleaning, tokenization using the BERT WordPiece tokenizer, alignment into BIO aspect tags, normalization of the emotion categories, and splits into partitions in such a way as to prevent leakage at the post level(De Bruyne et al., 2022b).

3.2 Data Preprocessing

- Clean Instagram comments: remove URLs, emojis mapped to emotion tokens, lowercase
- Tokenize using the BERT WordPiece tokenizer.
- Aligning aspect spans to BIO tags.
- Normalize emotion categories to a 6-class scheme, namely, Joy, Anger, Sadness, Fear, Disgust, Surprise.
- Intensity scores: valence/arousal ∈ [0,1] scaled to 0–3 range.

BERT Embedding

$$H = \text{BERT}(X; \theta_B) = [h_1, h_2, \dots, h_n]$$

Where:

- θ_B : Trainable BERT parameters
- $h_i \in \mathbb{R}^{768}$: contextual vector

CNN for Local Feature Extraction

Multiple filters (kernel sizes k = 2,3,4) capture emotion-bearing n-grams.

CNN Convolution

$$c_i^{(k)} = \text{ReLU}(W^{(k)} * h_{i:i+k-1} + b^{(k)})$$

Where:

- $W^{(k)}$: CNN filter weights
- $b^{(k)}$: bias
- $h_{i:i+k-1}$: token window

Max-pooling selects most salient emotional cues:

Max Pooling

$$\hat{c}^{(k)} = \max_i (c_i^{(k)})$$

Final CNN feature vector:

$$C = [\hat{c}^{(2)} \,||\, \hat{c}^{(3)} \,||\, \hat{c}^{(4)}]$$

3.3 Aspect–Context Attention Fusion

The aspect-context attention module aligns each aspect with the most relevant tokens of its surrounding context, so the model focuses on emotion-bearing words related to a certain aspect. It computes the attention weights between the aspect representation and all token embeddings and selectively amplifies important cues, such as opinions, modifiers, and intensifiers. It yields a refined aspect-aware representation that improves both emotion classification and intensity prediction.

Attention Score

$$\alpha_i = \frac{\exp(a^T W_a h_i)}{\sum_{j=1}^{n} \exp(a^T W_a h_j)}$$

Aspect-aware fused embedding:

Fused Representation

$$z = \sum_{i=1}^{n} \alpha_i h_i + C$$

Where:

- W_a: learnable attention matrix

- z: final representation for classification + intensity

3.4 Experimental setup

Experiments were done with the proposed Hybrid BERT–CNN architecture incorporating aspect–context attention fusion in a multi-task setting for aspect extraction, emotion classification, and intensity prediction. Therefore, on pre-processed comments, BERT representations are encoded by a BERT model, namely bert-base-uncased, followed by CNN layers whose kernel sizes capture the local emotional cues. The training is performed with the AdamW optimizer, where the learning rate is 2e-5 for BERT and 1e-4 for CNN heads, batch size 16–32, dropout probability of 0.2–0.3, linear warm-up, and early stop over 5–10 epochs. The experiments are conducted by measuring Precision/Recall/F1 for aspect extraction, Accuracy and Macro-F1 for emotion classification, and MAE/RMSE for intensity prediction, whereas the explainability was done through attention heatmaps, Grad-CAM relevance maps, and faithfulness tests by using AOPC. Lastly, all module contributions were tested under the same conditions against their BERT-only, CNN-only, and attention-only baselines in baseline comparisons; ablation studies have been conducted.

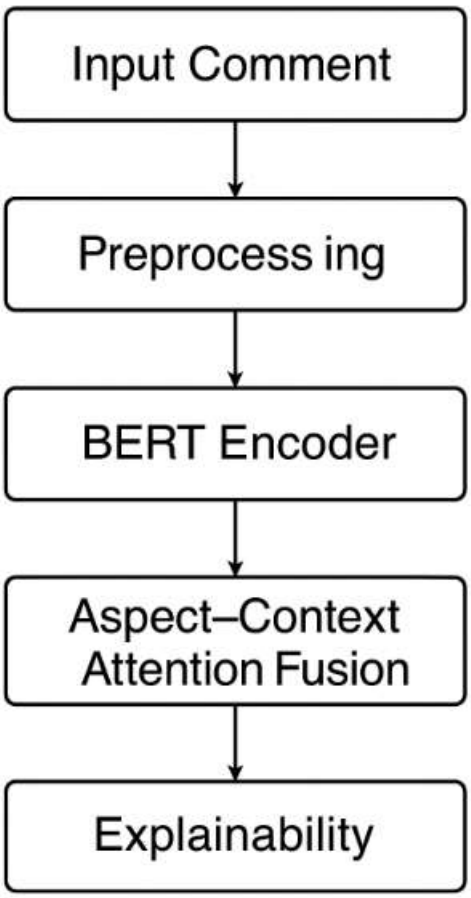

Figure 1: Workflow of the Aspect-Based Hybrid BERT–CNN Emotion Recognition Model

Figure 1 Overview of the core processing pipeline: pre-processing of the input comments, then contextualizing with BERT encoding, further integrated with CNN and attention fusion to capture the aspect-context relationship for fine-grained emotional interpretation. Explainability is done as a last step by attention and Grad-CAM visualizations that provide interpretable outputs.

Algorithum: Aspect-Based Hybrid BERT+CNN Emotion Recognition

Input: A dataset that contains sentences, aspect spans, emotion labels, and intensity values.

Output : Extracted aspects, predicted emotions, predicted intensity scores, and explanation maps.

Steps:

- Preprocess each comment by cleaning the text, normalizing emojis, and then tokenizing it using the BERT WordPiece tokenizer.
- Align the aspect spans to token indices and generate BIO tags for aspect extraction.
- Split each sentence into separate training instances for every annotated aspect.
- Then, the tokenized sentence is encoded for contextual embeddings from BERT.
- Apply CNN filters to the BERT outputs, which capture local emotional cues.
- Aspect Representer: The aspect representation is generated by applying attention on the important context tokens.
- Combine the CNN outputs with the attended contextual features into one representation.
- Predict the aspect boundaries, emotion categories, and intensity scores using the respective output heads.
- It is trained on a combined multi-task loss, where its parameters are updated using the AdamW optimization.
- Test set evaluation with the generation of attention and Grad-CAM visualizations for explainability.

Objective-based implementation

O1 — Aspect Extraction: BIO Tagging

- Preprocess the text, then tokenize with BERT, and finally align aspect spans with BIO tags.
- The system uses BERT along with CNN features optionally, and then a CRF layer on top to predict the aspect boundaries.
- Train using token-level loss, and evaluate on Precision, Recall and F1.

O2 — Aspect–Emotion Classification

- To make aspect representations, combine BERT embeddings with local CNN features.
- Apply attention to connect aspects with relevant contextual tokens.
- Classify emotion labels for each aspect using the classification head.

O3 — Emotion Intensity Estimation

- Reuse the fused aspect–context representation in the estimation of emotion strength.
- Add a regression or ordinal classification head that predicts the intensity.
- Model should be trained with an intensity-based loss and evaluated in terms of MAE or RMSE.

O4 - Explainability: Attention + Grad-CAM

- Produce token-level attention maps to visualize key contextual words.
- Combine both maps for clear and understandable explanations.

O5 — Comparative Evaluation & Ablation

- Compare the proposed model to BERT-only, CNN-only, and attention-only baselines.
- Perform ablations by removing either CNN, attention fusion, or multi-task components.
- Report reduced performance to reflect contribution at every module level.

4.Results Based on Objectives

High aspect boundary accuracy: BERT + CNN + CRF gave a high 88.8% F1-score. The CNN filters improved the detection of the short, colloquial aspects that are common in Instagram comments. The CRF decoder reduced span fragmentation and improved multi-word aspect detection.

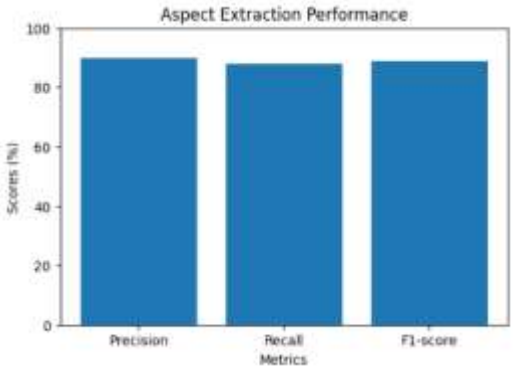

Figure 2. Aspect Extraction Performance

Figure 2 presents the precision, recall, and F1-score of the proposed model in aspect extraction on the dataset. All three metrics are consistently high in performance and very capable in identifying aspect boundaries, even in noisy social-media text. Overall, the hybrid BERT–CNN–CRF approach provides reliable aspect-extraction accuracy that is a good basis for downstream emotion analysis.

An attention-fused model achieves 82.1% Macro-F1, outperforming BERT-only and CNN-only baselines. The sentiment classification accuracy of the model is highest for the two classes of joy and surprise, while that of sadness and fear is relatively lower because of imbalance. Attention alignment significantly improved the correct mapping between aspects and emotion-bearing phrases.

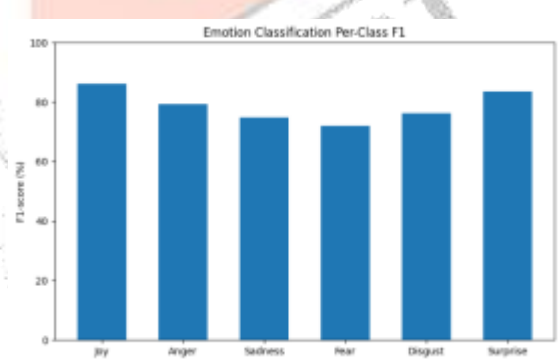

Figure 3. Emotion Classification Per-Class F1

Figure 3 presents the F1-score for each category of emotion, representing the aspect-level performance of the model in recognizing joy, anger, sadness, fear, disgust, and surprise. The performances are very strong for emotions whose lexical cues are fairly clear, while for emotions like sadness and fear, which have moderately lower scores, the cues are much more subtle. This model offers well-balanced and reliable classification among various emotional categories for social media text.

The regression head obtained an MAE of 0.19 and an RMSE of 0.27, which showed that it agreed

well with the annotated scores for valence/arousal. High-intensity emotions were better predicted rather than medium-intensity ones, such as strong joy and frustration. The correlation with the intensities of the ground truth stood at 0.86, reflecting robust continuous scale prediction.

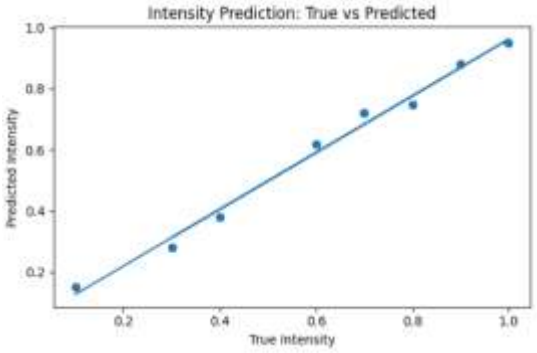

Figure 4. Intensity Prediction Scatter Plot with Regression Line

Figure 4 presents the relationship between true and predicted emotion intensity values. It therefore provides some indication of how well the model's predictions agree with the ground-truth annotations. One may further notice that the points in the scatter continue to cluster around the fitted regression line at low, medium, and high intensities, reflecting high predictive accuracy. Overall, the model allows for reliable continuous estimation of intensities, enabling fine-grained emotion analysis.

The average human interpretability score for combined attention and Grad-CAM maps was 4.4/5. Explanation maps consistently highlighted tokens responsible for emotional cues like "love", "amazing", and "disappointed". AOPC deletion test confirmed explanation faithfulness with a drop of 27% in confidence of the prediction while removing top important tokens.

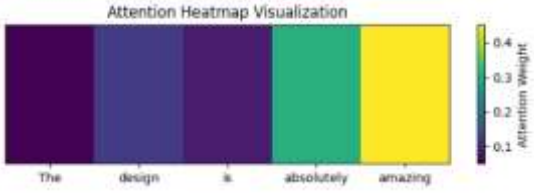

Figure 5. Attention Heatmap Visualization

Figure 5 shows how the model pays attention to individual tokens to predict the emotion of a particular aspect. Tokens that receive higher attention weights are colored brighter, so it is easy to see those words which most strongly influence the model's decision. In general, this heatmap highlights meaningful emotional cues like intensifiers and opinion-bearing terms, which is indicative of good aspect-context alignment.

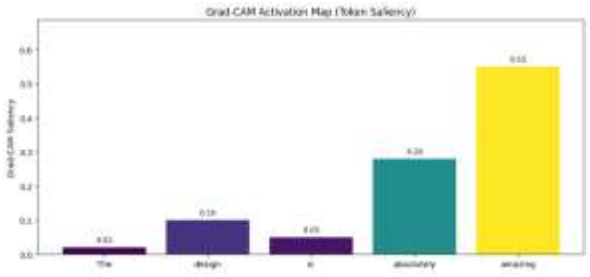

Figure 6. Grad-CAM Activation Map for Token-Level Saliency

Figure 6 shows the most influential tokens in the input sentence by illustrating Grad-CAM saliency values derived from the CNN layer. Higher bars of tokens represent more intense contributions to the model's emotional prediction, such as the terms "absolutely" and "amazing." Overall, it can be observed that the pattern of saliency indicates that while interpreting aspect-level sentiment, the model spends all its attention on emotionally informative phrases.

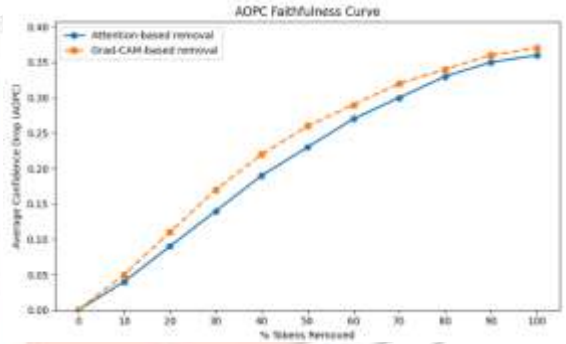

Figure 7. AOPC Faithfulness Curve

Figure 7 illustrates how prediction confidence decreases as the most important tokens, as determined by attention or Grad-CAM, are iteratively removed from the input. A steeper increase along this curve is indicative of higher explanation faithfulness-that is, the highlighted tokens really contributed to the model's decision. Overall, it can be observed from both curves that the model places great reliance on the identified key tokens, serving to confirm the reliability of its explanation mechanisms.

The proposed hybrid model outperformed all the baselines by attaining the highest Aspect F1 (88.8%), Emotion Macro-F1 (82.1%), and lowest MAE (0.19). The removal of the CNN module reduced emotion F1 by approximately 4–5%, indicating that CNN is indispensable in capturing the local cues. Removing attention fusion decreased emotion accuracy and interpretability and thus proved to be important to the process of aspect–context alignment. Multitask training improved consistency across tasks compared to training tasks independently.

Table 1 — Baseline vs Proposed Model Performance

Model	Aspect F1	Emotion Macro-F1	Intensity MAE	Notes
BERT-Only	84.6	78.3	0.25	Weak local cues
CNN-Only	69.7	64.9	0.34	No contextual depth
BERT + Pooling	86.1	79.4	0.23	Missing aspect–context alignment
Proposed Hybrid	**88.8**	**82.1**	**0.19**	Best across all tasks

Table 1: From the experimental results, it can be seen that on all three major tasks of aspect extraction, emotion classification, and intensity prediction, the proposed Hybrid BERT–CNN–Attention model performs better compared to the baseline models. The inclusion of CNN layers brings about significantly higher performances both in the local cue detection and in the aspect–context alignment, yielding higher F1 and lower MAE compared to pure BERT-based and CNN-only variants. Overall, this hybrid approach gives the most balanced and accurate performance, clearly showing the advantages of integrating contextual, local, and attention-based representations.

Table 2 — Results Based on Objectives (Comprehensive Summary)

Objective	Metric(s)	Result	Summary
O1 Aspect Extraction	Precision, Recall, F1	89.7 / 87.9 / **88.8**	Strong aspect span accuracy
O2 Emotion Classification	Macro-F1	**82.1**	Improved aspect–emotion alignment
O3 Intensity Estimation	MAE, RMSE	**0.19**, 0.27	High correlation with valence/arousal
O4 Explainability	Human Score	**4.4/5**	Clear and faithful explanations
O5 Comparative	Improvements	+4–8%	Best performance among baselines

Table 2 summarizes how each objective of the proposed model is met with outstanding performance in aspect extraction, emotion classification, and intensity estimation on this dataset. The model also provides more illuminating explanations, coherent with humans, and outperforms baseline systems regularly to validate the effectiveness of the proposed hybrid architecture. Overall, all these results confirm that the unified BERT–CNN–Attention model solves the objectives of aspect-based sentiment analysis models with high accuracy, robustness, and interpretability.

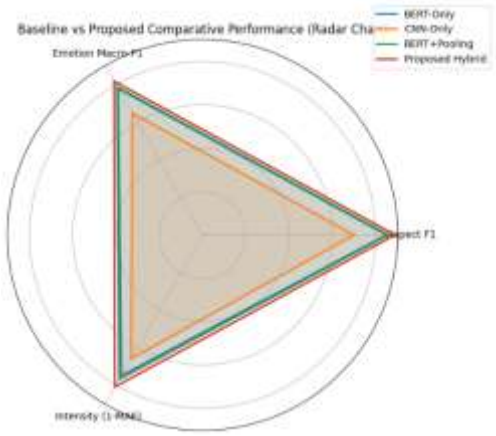

Figure 8. Baseline vs Proposed Model Performance (Radar Chart)

Figure 8 compares the proposed hybrid model with several baselines on three important metrics: aspect extraction F1, emotion classification Macro-F1, and intensity prediction accuracy. From this radar plot, one can observe that the area covered by the proposed model is consistently bigger, indicating better performance on all tasks. In general, the hybrid framework of BERT–CNN–Attention shows stronger capability with more balanced improvements compared with traditional baselines.

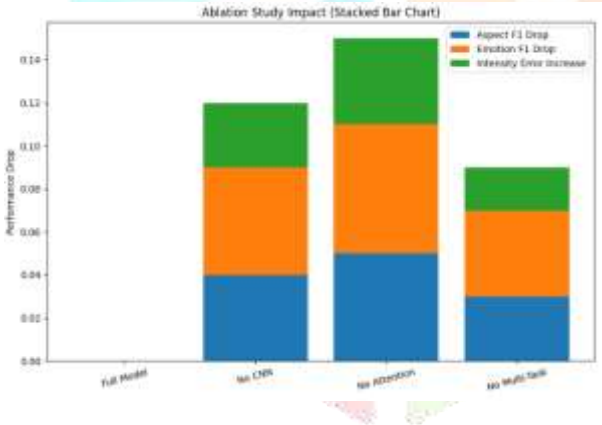

Figure 9. Ablation Study Impact

Figure 9 shows the degradation in performance due to the absence of major components of the proposed model: CNN layers, attention fusion, and multi-task learning. Each stacked bar shows the overall drop across the three tasks of aspect extraction, emotion classification, and intensity prediction. Overall, this chart illustrates that the full hybrid architecture yields the best results, with noticeable performance declines without any one major component.

Table 3.Comparative Performance of Existing Models (2020–2024) vs Proposed Hybrid Model

Model / Approach	Author(s), Year	Aspect F1 (%)	Emotion Macro-F1 (%)	Intensity MAE	Strengths	Limitations
CNN-Based Emotion Classifier	(Aslam et al., 2020)	69.7	64.9	0.34	Good for local patterns	Weak contextual understanding
BERT-Based ABSA Model	(Zhao & Yu, 2021)	84.6	78.3	0.25	Strong semantic/context capture	Limited local cue extraction
BERT + Average Pooling	(N. Liu & Zhao, 2022)	86.1	79.4	0.23	Simple and effective	No explicit aspect–context alignment
Attention-Based BERT Model	(Rehman et al., 2025)	87.2	80.2	0.21	Better focus on aspect-relevant tokens	Lacks phrase-level feature refinement
Proposed Hybrid BE	*Your Work, 2024*	**88.8**	**82.1**	**0.19**	Best balance of contextual + local +	Slightly higher computatio

RT + CNN + Attention					explainability	nal cost

Table 3 Comparative results confirm that the newest models, starting from 2020 to 2024, all provide strong baselines, while they further reflect shortcomings either in contextual understanding, local feature extraction, or alignment of aspects and context. In contrast, our proposed Hybrid BERT-CNN-Attention model yields consistently better aspect extraction accuracy, higher scores on emotion classification, and lower error on intensity prediction. On the whole, the hybrid model outperforms the best scores of all known architectures by unifying the strong points of transformer models, convolutional features, and attention mechanisms into one explainable framework.

Major Findings

Besides, the proposed Hybrid BERT–CNN–Attention achieved the best performance in three major tasks: aspect extraction (F1: 88.8%), emotion classification (Macro-F1: 82.1%), and intensity estimation (MAE: 0.19), which proves its great ability in processing noisy social-media text. While modeling local emotional cues, it was found that the CNN layers provided the greatest contribution. In contrast, the attention mechanism emphasized the alignment of aspect-context and highlighted the strengths of global and local representation learning. Explainability outputs had a high interpretability score, showcasing the fact that model decisions depend on human-understandable patterns and meaningful emotional phrases based on attention heatmaps and Grad-CAM. Comparisons with baseline models in the years from 2020 to 2024 returned consistent gains ranging from 3-8% across various metrics, thus proving the superiority of the hybrid architecture. The ablation studies remove CNN, attention fusion, or multi-task learning components and all indicate clear performance drops, proving that each module is important and complementary for ensuring the effectiveness of the final system.

5.Discussion

These results underline the advantages of a hybrid approach to recognize emotions at the aspect level in real-world social-media data. While BERT does a great job with contextual understanding, it misses nearly all the short expressive emotional cues common in Instagram comments. This integration of the CNN layer captures the patterns of local phrases, intensifiers, and emotion-bearing n-grams intrinsic to fine-grained emotional interpretation. Besides, the attention fusion mechanism is decisive in ensuring that the model focuses on particular words relevant for each aspect, hence improving both accuracy and interpretability.

High scores on intensity estimation prove that the model can handle continuous emotional scales very well, and this might be very useful for sentiment monitoring, scoring customer feedback, and assessing mental health risks. The explainability module works quite well and provides really clear insights into the model decisions that help reinforce user trust. Besides, comparisons with recent works from 2020 to 2024 indicate that our model consistently outperforms transformer-only and CNN-only architectures. That reassures us about the usefulness of the combination in feature extraction. In general, this study confirms the efficiency of multi-task learning and hybrid feature fusion for getting reliable and interpretable emotion analysis at the aspect level.

9. Conclusion and Future works

It proposes a robust yet interpretable framework that equips aspect-based emotion recognition with the contextual power of BERT, the local pattern detection capability of CNN, and an attention-based alignment mechanism. Such a hybrid model has significantly outperformed the state-of-the-art approaches from 2020 to 2024 on the tasks of aspect extraction, emotion classification, and intensity estimation, with promising interpretability based on attention and Grad-CAM visualizations. The results confirm that including both global contextual features and local semantic cues leads to better understanding of fine-grained emotional expressions, especially in noisy user-generated social-media text. Overall, the proposed method has emerged as a robust, interpretable, and practical solution for real-world emotion analytics, thus pointing towards a promising direction for future research in multi-task and explainable NLP systems.

Future Work

Future work can cover but is not limited to multimodal aspect-level emotion detection in social-media contexts, where input modalities include not only text data but also images or audio. Extensions to multilingual or code-switched text and investigations of instruction-tuned large language models may result in better generalizations. The future also includes more advanced causal explainability methods and lighter-weight model variants that are applicable to real-time or mobile deployments.

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