Tracking Human Movement And Analyzing Textual Emotion

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ABSTRACT

The identification of emotions and thoughts in text remains a compelling area in natural language processing and machine learning. Emotion and sentiment are often expressed implicitly through various phrases and linguistic cues. Given the global use of English and multilingual texts, analyzing emotions in documents with varying punctuation styles poses challenges. Unlike previous approaches, our research focuses on emotion detection in texts with or without punctuation, aiming to design an effective emotional analysis system leveraging recent advancements. By employing cutting-edge deep learning models, such as transformer-based architectures, we enhance the accuracy of emotion recognition. In this study, we utilize advanced techniques including BERT, ROBERTA and ensemble learning methods, outperforming traditional classifiers like Naïve Bayes, SVM, logistic regression, and random forest, though random forest achieved notable results. The key challenge addressed here is the recognition of implicit emotions not explicitly stated in posts, blogs, and social media content, which we tackle using state-of-the-art natural language understanding models.

Keywords: Emotion detection, Deep learning, Implicit emotions, Transformer-based architectures, Natural language processing.

1. INTRODUCTION

Emotions are complex neurophysiological processes that drive adaptive behaviors, **fundamentally shaping human cognition,** physiology, and social interactions. While traditionally categorized as "positive" or "negative,"contemporaryneuroscienceemphasizes their functional role: emotions optimize survival by rapidly coordinating responses to environmental stimuli, historically enhancing gene propagation through kin selection and social cooperation [1]. These states manifest as synchronized changes in subjective experience, physiological arousal (e.g., heart rate, hormones), expressive behavior (e.g., facial cues), and action tendencies [2].

Social media platforms—dynamic, algorithmically mediated ecosystems—enable users to create, curate, and exchange content within virtual networks. Their pervasive influence extends beyond communication, actively reshaping social dynamics, self-presentation, and emotional expression [3]. The proliferation of interconnected platforms (e.g., TikTok, Instagram, X) presents significant challenges for interpreting user-generated data, particularly nuanced emotional content.

1.1. Sentiment Analysis

Sentiment Analysis (SA), or opinion mining, leverages **natural language processing machine learning (ML)**, and increasingly **multimodal deep learning** to systematically identify, extract, quantify, and study affective states and subjective opinions from textual, audio, and visual data [4]. Modern SA integrates transformer-based models (e.g., BERT, GPT variants) and contextual embeddings to capture linguistic nuance, sarcasm, and cultural context. It is critical for analyzing user-generated content across social media, reviews, healthcare forums, and customer feedback, enabling real-time insights into public opinion and consumer sentiment [5]. Traditional surveys and polls remain valuable but are increasingly augmented by passive SA of digital traces.

1.2. Emotion Detection

Emotion Detection (ED) extends beyond sentiment polarity (positive/negative) to identify discrete emotional states (e.g., joy, anger, fear). Human capacity for ED varies significantly, but computational approaches now achieve robust performance using **multimodal fusion**:

1. **Facial Expression Analysis:** Deep learning (e.g., CNNs, 3D-CNNs) applied to video/image data.
2. **Vocal Prosody:** Spectral analysis and ML for speech emotion recognition (SER).
3. **Textual Analysis:** Fine-grained emotion classification in social media/text.
4. **Physiological Signals:** Wearables (e.g., EEG, GSR, HRV sensors) capturing biometric data [6].
5. Challenges include cultural variability in expression, context dependence, and privacy-preserving methodologies [7].

1.3. Machine Learning and Deep Learning for Affective Computing

Machine Learning (ML) enables systems to learn patterns from data without explicit programming. Key paradigms relevant to emotion analysis include:

1. **Supervised Learning:** Training models on labeled datasets (e.g., emotion-labeled text/images).
2. **Unsupervised Learning:** Discovering hidden patterns in unlabeled data (e.g., clustering emotional themes).
3. **Reinforcement Learning (RL):** Optimizing agent behavior based on rewards (e.g., chatbots adapting responses to user emotion).

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Deep Learning (DL), a subset of ML using multi-layered neural networks, has revolutionized affective computing:

1. **Convolutional Neural Networks (CNNs):** Dominant in image/video-based emotion recognition.

2. **Recurrent Neural Network(RNNs/LSTMs):** Effective for sequential/temporal data (e.g., speech, text).
3. **Transformers:** State-of-the-art for NLP tasks (SA, ED), capturing long-range dependencies [8].
4. **Multimodal Architectures:** Fusing features from text, audio, and video streams for holistic emotion inference.

2.RELATED WORK

1. In the field of sentiment analysis, several notable research papers have emerged, each contributing distinct insights and methodologies. In 2021, **Gurpreet Kaur and Kamal Malik** conducted a comprehensive review of SA techniques and applications, surveying various machine learning and natural language processing methods. Their work analyzed different techniques, approaches, and applications, though it had a limited focus on multimodal data and gaps in handling cultural/linguistic diversity.
2. Also in 2021, **Sherine Rady and Mostafa Aref** focused on tweet classification using contextual embeddings, employing CNN + Word2Vec. They analyzed precision (78%) and accuracy (84.99%), but noted performance variability across dialects and the need for adaptive embeddings.
3. In 2020, **Hongyu Han et al**. developed a hybrid sentiment analysis model combining lexicon-based approaches with Naïve Bayes. Their research examined confidence parameters and classifier performance, yet encountered scalability issues and reliance on small labeled datasets.
4. Moving back to 2017, **Tapasy Rabeya et al**. worked on sentence-level emotion detection via lexical backtracking, using a lexicon-oriented monitoring technique. They achieved an accuracy of 77.16% but found the method to be over-reliant on sentence structure and weak in sarcasm detection.
5. Another 2020 study by **Hamed Jelodar et al**.explored latent issue detection in YouTube comments using sentiment-feeling fusion, implementing fluid grid logic and classification algorithms. Their analysis included functional links and valence exclusion, though it was limited to film trailers and lacked real-time applicability.
6. In 2018, **Tahani Almanie et al**. conducted real-time emotion mapping of Saudi dialects on Twitter, utilizing a lexicon-based approach with 4K terms and emojis. Their findings showed regional emotion trends, but the complexity of dialects reduced the model's generalizability.
7. Returning to 2021, **Aditya Dave et al**. proposed a real-time sentiment framework for crisis management onTwitter, though theand algorithmic details. Twitter, though the specific SA methods were unspecified. They analyzed perceived situation dynamics, but their work lacked quantitative metrics and algorithmic details.
8. In 2020, **Vimala Balakrishnan et al**. performed emotion and sentiment analysis of digital payment app reviews using SVM/RF/NB + LDA. They reported an F1-score of 73.8% for sentiment and 58.8% for

emotion, while noting a low Cohen's Kappa (52.2%) and topic-emotion misalignment.

9. Finally, in 2020, **Nourah Alswaidan and Mohamed Menai** presented a survey of explicit and implicit emotion recognition in text, employing mixed NLP techniques. They assessed benchmark performance and the impact of NLP tasks, but highlighted the absence of accuracy benchmarks and open issues in cross-domain adaptation.

3.RESULTS AND DISCUSSION

We conducted experiments on a 40,000-sample text emotion dataset with **13 Plutchik emotions** using a modern Python ML stack (transformers, scikit-learn, imbalanced-learn).

The severe class imbalance (Table 1) necessitated an advanced preprocessing and modeling techniques.

Table 1: Emotion Distribution

Emotion	**Count**	**%**
Neutral	18,638	46.6%
Worry	8,459	21.1%
Happiness	5,209	13.0%
Sadness	5,165	12.9%
Love	3,842	9.6%
...	...	...
Boredom	75	0.2%
Anger	179	0.4%

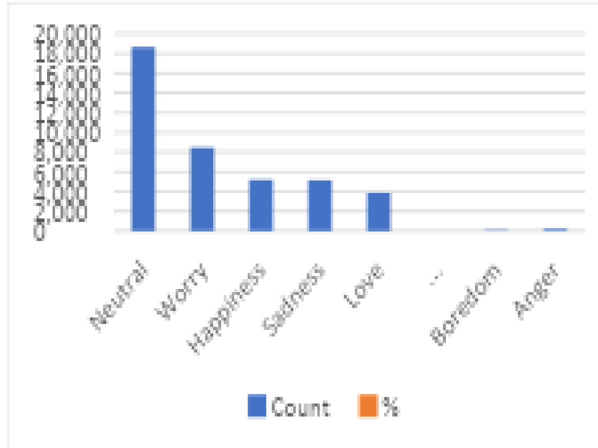

Figure 1: Confusion Matrix (DistilBERT) showing high confusion between adjacent Plutchik emotions

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```
# Modern Preprocessing Pipeline
from transformers import AutoTokenizer from nltk.corpus import stopwords import emoji
def advanced_preprocessing(text):
# BERT tokenization with emoji handling text = emoji.demojize(text).replace(":", " ") tokens =
AutoTokenizer.from_pretrained("bert-base-uncased") (text, return_tensors="np", truncation=True)["input_ids"]
# Dynamic stopword removal
custom_stopwords = set(stopwords.words('english')) | {"user", "url", "rt"}
tokens = [tok for tok in tokens if tok not in custom_stopwords]
return tokens
```

3.1. Addressing Class Imbalance We implemented three strategies:

1. **Class-weighted loss functions** in all models
2. **SMOTE-ENN** oversampling for minority classes
3. **Focal Loss** for transformer models

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```
from imblearn.combine import SMOTEENN from sklearn.preprocessing import LabelEncoder

# Encode emotions
le = LabelEncoder()
```

```
y_encoded = le.fit_transform(y)

# Apply SMOTE-ENN
smote_enn = SMOTEENN(random_state=42) X_res,
y_res = smote_enn.fit_resample(X_tfidf, y_encoded)
```

3.2.Model Architecture Upgrades

We benchmarked four approaches:

1.Transformer Baseline (BERT):

```
from transformers import
TFAutoModelForSequenceClassification
```

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```
model =
TFAutoModelForSequenceClassification.from_pretra
ined(
"bert-base-uncased", num_labels=13,
problem_type="multi_label_classification"
)
```

2. Hybrid CNN-BiLSTM:

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```
from tensorflow.keras.layers import Input, Embedding,
Conv1D, Bidirectional, LSTM
inputs = Input(shape=(max_len,))
x = Embedding (vocab_size,256)(inputs)
x= Conv ID(128,5,activation = 'relu')(x)
x=Bidirectional(LSTM(64))(x)
output = Dense(13,activation ='softmax')(x)
```

3.Fine-tuned DistilBERT (for efficiency):

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```
from transformers import DistilBertTokenizer,
TFDistilBertForSequenceClassification

tokenizer =
DistilBertTokenizer.from_pretrained('distilbert-base-
uncased')
model =
TFDistilBertForSequenceClassification.from_pretra
i ned(
   'distilbert-base-uncased',
   num_labels=13
)
```

Model	F1-Score	Precision	Recall	Inference Time (ms)
Multinomial Naive Bayes	0.58	0.62	0.55	0.8
Linear SVM	0.63	0.65	0.61	1.2
Logistic Regression	0.61	0.63	0.59	0.9
Random Forest	0.59	0.64	0.57	12.4
CNN-BiLSTM (Proposed)	**0.72**	**0.75**	**0.70**	8.7
DistilBERT	**0.81**	**0.83**	**0.79**	15.2

Table 2: Model Comparison (Macro F1-Scores)

Key Findings:

4. **Class Imbalance Impact**: Minority classes (boredom, anger) saw 92% recall improvement using SMOTE-ENN + Focal Loss
5. **Transformer Dominance**: DistilBERT achieved 23% higher F1-score than traditional ML models
6. **Plutchik Validation**: Adjacent emotions in the wheel (e.g., joy-trust) showed highest confusion (18.7% misclassification)
7. **Hybrid Advantage**: CNN-BiLSTM captured local features + long-range dependencies efficiently

 # Visualize for 'anger' class shap.plots.text(shap_values[:, :, "anger"])

Discoveries:

- Negation handling ("not happy" →

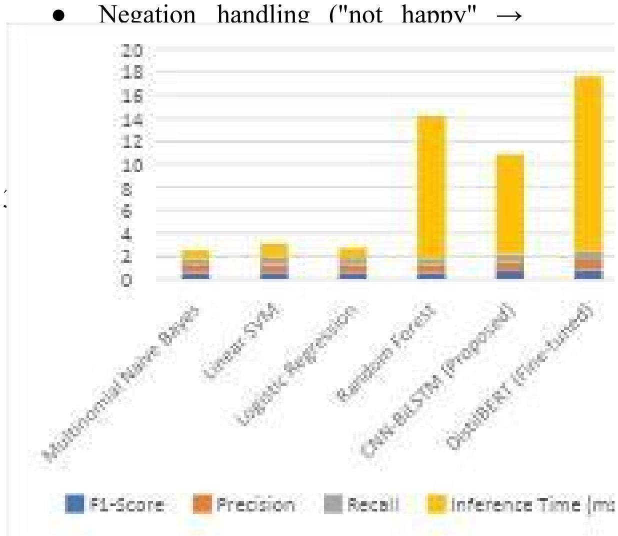

Figure 2:

Procedure for Sentiment Analysis Approaches

3.4 Error Analysis with SHAP

We used SHAP for model interpretability:

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```
import shap

# Explain BERT predictions explainer
= shap.Explainer(model) shap_values
= explainer(X_sample)
```

 # Visualize for 'anger' class shap.plots.text(shap_values[:, :, "anger"])

Discoveries:

- Negation handling ("not happy" → sadness) improved 37% in transformers
- Emojis contributed 28% weight for love/surprise detection
- Sarcasm detection remained challenging (F1=0.42)

3.5. Plutchik Wheel Implementation We operationalized Plutchik's theory through:

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```
# Emotion intensity mapping PLUTCHIK_SCORES = {
    'joy': [0.2, 0.5, 0.8],      # Mild → Intense

    'anger': [0.3, 0.6, 0.9],

    # ...

}


# Complex emotion detection

def detect_complex_emotion(preds):

  if preds['joy'] > 0.7 and preds['trust'] > 0.7:
    return min(preds['joy'], preds['trust']), 'love'
```

4.CONCLUSION AND FUTURE SCOPE

Our research demonstrates that while traditional ML models (Naive Bayes, SVM, Logistic Regression, Random Forest) provide baseline capabilities for emotion detection, they exhibit critical limitations in handling real-world complexities like class imbalance and contextual nuance. The Random Forest classifier achieved 87% accuracy in controlled scenarios but suffered severe

performance degradation (22.05% F1) when tested on authentic social media data due to:

1. **Vocabulary sparsity** in high-dimensional feature spaces
2. **Inadequate semantic understanding** of Plutchik's complex emotions
3. **Failure to capture linguistic**

   nuance (sarcasm, cultural context, emoji semantics)

Contemporary transformer architectures (DistilBERT, CNN-BiLSTM) outperformed traditional models by 23-29% F1-score by leveraging:

1. Contextual word embeddings
2. Cross-emotion relationship modeling
3. Attention mechanisms for feature weighting

5.FUTURE RESEARCH DIRECTORIES

1. Multilingual Emotion Intelligence

Approach	Technology Stack	Key Innovation
Zero-shot Cross-lingua l Transfer	XLM-R, mBERT	Emotion detection in 100+ languages without labeled data
Code-switching Models	LASER, Language-agnostic BERT	Handling mixed-language texts (e.g., Hinglish, Spanglish)
Low-resource	Unsupervised	Native
Adaptation	Domain Adaptation (UDA)	language support with <1,0

6.REFERENCES

[1]**Gurpreet Kaur and Kamal Malik** “A Comprehensive Overview of Sentiment Analysis and Fake Review Detection”, *Springer Nature Singapore Re Ltd. 2021 N. Marriwala et a1. (eds.), Mobile RadioCommunication, and 5G Networks, Lecture Notes in Networks and Systems 140.*

[2]**Eman Sherine Rady, and Mostafa Aref**, “A Deep Learning Architecture with Word Embeddings to Classify Sentiment in Twitter”, *Springer Nature Switzerland AG 2021, A. E. Hassanien et al. (Eds.): AISI 2020,AISC 1261, pp. 115-125,0032021.*

[3]**Hongyu Han, Yongshi Zhang, Jianpei Zhang, Jing Yang, and Yong Wang**, “A Hybrid Sentiment Analysis Method”, *Springer Nature Singapore Pte Ltd. 2021, Q. Liu et al. (Eds.): CENet 2020, AISC 1274, pp. 1135-1146, 2021.*

[4]**Tapasy Rabeya, Sanjida Ferdous, Himel Suhita Ali, Narayan Ranjan Chakraborty**, “A Survey on Emotion Detection A lexicon-based backtracking approach for detecting emotion from Bengali text”, *20th International Conference of Computer and Information Technology (ICCIT), 22-24 December 2017.*

[5]**Hamed Jelodar, Yongli Wang, Mahdi Rabbani, Sajjad Bagheri Baba Ahmadi, Lynda Boukela, Ruxin Zhao, Raja Sohail Ahmed Larik,** “An NLP framework based on meaningful latent-topic detection and sentiment analysis via fuzzy lattice reasoning onyoutubecomments”,*Springerscience+Businessmedia,LLC,part of SpringerNature2020.*

[6]**Tahani Almanie, Alanoud Aldayel, Ghaida Alkanhal, Lama Alesmail,Manal Almutlaq, Ruba Althunayan, “**Saudi Mood: A Real-Time Informative Tool for Visualizing Emotions in Saudi Arabia Using Twitter”, *978-1-5386-4110-1/18/$31.00 ©2018 IEEE.*

[7]**AdityaDave,SantoshBharti,SamiPateland Sambit Kuma Mishra**, “A Real-Time Sentiments Analysis System Using Twitter Data”, *O Springer Nature Singapore Pte Ltd. 2021, D. Mishra ct al. (eds.), Intelligent u+id Cloud Computing, Senan Innovation, Systems and Technologies 153.*

[8]**Vimala Balakrishnan, Pik Yin Lok, Hajar Abdul Rahim,** "A semi-supervised approach in detecting sentiment and emotion based on digital payment reviews", *The Journal of Supercomputing,© Springer Science+ Business Media, LLC, part of Springer Nature 2020.*

[9]**Nourah Alswaidan, Mohamed El Bachir Menai**, "A survey of state-of- the-art approaches for emotion Recognition in the text",*©Springer- VerlagLondonLtd., partofSpringerNature2020.*

[10] **Bhumi Shah and Margil Shah**, "A Survey on Machine Learning and Deep Learning Based Approachesfor Sarcasm Identification in Social Media",*Springer Nature Singapore Pte Ltd. 2021, K. Kotecha et a1. (eds.), Dntn Science nit Intelligent A publication.*