EVALUATING THE EFFECTIVENESS OF DISTILBERT FOR SENTIMENT ANALYSIS OF PLAYER FEEDBACK IN GAME DEVELOPMENT

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ABSTRAK

Real-time sentiment analysis (SA) plays an increasingly vital role in enhancing player experience through emotion-aware game design. By enabling systems such as dynamic difficulty adjustment, adaptive non-playable character (NPC) behavior, and responsive narrative progression, SA allows games to respond intelligently to player emotions. This study investigates the effectiveness of DistilBERT, a lightweight transformer-based language model, for multi-label emotion classification using the GoEmotions dataset, which includes 27 fine-grained emotion categories. The model's performance was evaluated in terms of classification accuracy and computational efficiency. Experimental results reveal that DistilBERT delivers surprisingly strong performance despite its reduced size, making it a viable candidate for real-time applications in resource-constrained environments. These findings indicate that lightweight transformer models can support emotionally adaptive gameplay without significant trade-offs in latency or accuracy. Future work will focus on integrating DistilBERT into a live game environment to assess its impact on player engagement and real-time system responsiveness.

***Keywords*- DistilBERT, Sentiment Analysis, Game Development, Player Emotions**

I. PENDAHULUAN

In game development, understanding player emotions is crucial for creating engaging and personalized experiences. Sentiment analysis (SA) can help detect emotions in player feedback, enabling real-time adjustments to game mechanics, NPC interactions, and even the storyline. For example, a frustrated player might receive in-game help or difficulty adjustments, while an excited player might be offered more challenges or rewards [1][2][3].

In modern game development, creating immersive and emotionally engaging experiences has become a central design objective. As games evolve into more interactive and narrative-driven platforms, understanding player emotions in real time has emerged as a valuable capability. Sentiment analysis (SA), a subfield of natural language processing (NLP), offers a promising avenue for interpreting player feedback and adapting gameplay elements such as non-player character (NPC) behavior, storyline progression, and difficulty scaling. By enabling emotion-aware systems, developers can create more personalized and responsive gaming experiences [4][5][15].

Traditional sentiment analysis approaches, such as lexicon-based methods, often struggle to capture the nuance and context of natural language, particularly in environments as dynamic and expressive as gaming. Transformer-based models, notably BERT (*Bidirectional Encoder Representations from Transformers*), have demonstrated significant improvements in various NLP tasks, including sentiment classification [10][14]. However, due to the computational demands of such models, their real-time applicability in game environments is limited.

DistilBERT, a distilled and lighter version of BERT, addresses this limitation by providing a more efficient architecture with reduced parameters and faster inference time, while maintaining competitive performance. This makes DistilBERT a suitable candidate for real-time sentiment analysis in resource-constrained settings, such as live game environments [2][9].

This study explores the use of DistilBERT for sentiment analysis of player feedback using the GoEmotions dataset, a comprehensive emotional classification resource containing 27 distinct emotion categories. The primary goal is to evaluate the effectiveness and feasibility of deploying DistilBERT in game development workflows where real-time emotional understanding is crucial. By doing so, this research aims to support the development of more adaptive, emotionally intelligent game systems.

Sentiment analysis plays a multifaceted role in modern game development, enabling real-time emotional responsiveness that enhances player engagement. One key application is Dynamic Difficulty Adjustment (DDA), where the game modifies its challenge level in response to detected emotions—for instance, lowering difficulty when signs of frustration are identified. Another use case is non-player character (NPC) behavior adaptation, where NPCs can respond empathetically by altering dialogue, offering support, or modifying their interactions based on the player's emotional state. Additionally, narrative personalization can be achieved by adjusting quests or storylines according to emotional cues, thereby creating a more immersive and tailored gameplay experience [16][17][18].

To support such emotionally adaptive systems, this study utilizes the GoEmotions dataset, which provides fine-grained annotation across 27 distinct emotion categories, including joy, anger, sadness, and surprise. This granularity allows for a deeper understanding of player sentiment compared to conventional binary sentiment datasets. Given its efficient architecture and strong performance on emotion classification tasks, DistilBERT is particularly well-suited for leveraging the richness of the GoEmotions dataset in real-time game environments. Its ability to balance accuracy with low computational overhead makes it an ideal candidate for integration into sentiment-driven game systems [22][23][28].

II. RELATED WORK

A. OVERVIEW OF SENTIMENT ANALYSIS IN NLP

Sentiment analysis, or opinion mining, is widely used in NLP to classify text based on emotional tone—ranging from positive and negative polarity to nuanced affective states (e.g., joy, anger, sadness). Traditional lexicon- based and classical machine learning approaches (e.g., SVM, logistic regression) are often limited in capturing contextual subtleties and deep semantic meaning.

Large pre-trained transformers like BERT have set new benchmarks in sentiment and emotion classification tasks. However, recent research has evaluated lighter alternatives such as DistilBERT and RoBERTa. For instance, in testing emotion classification on the SST- 5 dataset, DistilBERT incurred only moderate accuracy loss compared to BERT but offered substantially faster training times, while RoBERTa achieved state-of-the-art accuracy (~60.2%) [9][21].

Studies that are more recent have conducted head- to- head comparisons across transformer models, including DistilBERT, demonstrating that while RoBERTa often delivers highest accuracy, DistilBERT remains competitive and far more efficient in resource- constrained settings.

B. DISTILBERT: EFFICIENCY AND PERFORMANCE TRADE- OFFS

Introduced by [2], DistilBERT is a distilled version of BERT that reduces the parameter size by around 40% while retaining approximately 97% of BERT's language understanding capability and improving inference speed by roughly 60%. This transformer is thus particularly compelling for real-time applications where latency and computational cost matter.

[1] Showcased DistilBERT's scalability and domain adaptability, emphasizing its competitive accuracy and significantly reduced inference time when fine-tuned on custom datasets—highlighting its potential for real-world, real-time NLP systems

Another investigation comparing DistilBERT and RoBERTa on emotion classification in social media found that while RoBERTa reached superior accuracy (~92.7%), DistilBERT remained competitive and offered marked efficiency benefits [8]. Hybrid architectures that combine DistilBERT embedding is with recurrent layers (e.g., BiGRU and BiLSTM) were also studied: one hybrid (DistilBERT- GLG) improved DistilBERT's accuracy by 1.8% on a smaller dataset (~Apple reviews) and offered robust performance across datasets even without emoji processing [3].

C. SENTIMENT ANALYSIS IN GAME DEVELOPMENT

In recent years, Sentiment Analysis (SA) has emerged as a valuable tool in the realm of game development, providing a means to assess player emotions and tailor game experiences accordingly. By analyzing player feedback, games can adapt dynamically to the emotional states of players, offering a more engaging and immersive experience [30].

One of the early applications of sentiment analysis in gaming involved analyzing player reviews to refine game design. More recently, researchers have focused on real-time emotion detection during gameplay to adjust key aspects of the game, such as difficulty, NPC interactions, and narrative flow. The application of DistilBERT specifically within game development is under-explored. Nonetheless, the evidence from social media and customer-support domains suggests strong potential: DistilBERT can enable efficient emotion detection at scale, even in noisy or short-form textual data [29].

Given the demands of real-time adaptive game systems—such as detection of player frustration or delivery of dynamic responses—DistilBERT's combination of speed and accuracy is particularly relevant. Its suitability for fine-grained emotion detection (as seen with the 27-category GoEmotions dataset) positions it as an ideal candidate for integration into player- feedback systems, emotion- aware NPC behavior, and adaptive narrative mechanisms.

D. SENTIMENT ANALYSIS IN REAL-TIME GAMING APPLICATIONS

As the integration of emotion-aware systems becomes more prevalent in game development, sentiment analysis has emerged as a crucial tool for crafting interactive and personalized player experiences.

1. Real-Time Feedback in Multiplayer Games
   [22] Illustrated the application of NLP models for detecting player emotions in real-time multiplayer gaming environments. By processing in game textual or voice communications, games can adapt dynamically to the emotional states of players, thereby fostering more immersive gameplay that balances challenge and engagement without causing frustration or boredom.
2. Adaptive Player Engagement
   [18] Employed sentiment analysis to monitor player frustration in serious games—educational games designed to facilitate learning. Their findings revealed that identifying frustration through sentiment analysis enabled the implementation of targeted difficulty adjustments or feedback mechanisms, which in turn improved player persistence and motivation. This highlights the potential of sentiment analysis as a means to maintain player engagement and enhance learning outcomes.
3. Emotion-Based NPC Interaction
   [17] Investigated the role of sentiment analysis in shaping NPC behavior, demonstrating that NPC responses could be modified based on the emotional

tone detected in player input. This dynamic adjustment enables the creation of more responsive and personalized NPC interactions, enriching the player's sense of immersion and fostering a stronger connection with the game world.

E. USE OF PRETRAINED MODELS FOR EMOTION RECOGNITION

Recent advancements in fine-tuning lightweight transformer architectures have highlighted the potential of models such as DistilBERT for emotion recognition tasks. As a distilled variant of BERT, DistilBERT retains much of the original model's contextual representation capacity while offering improved efficiency and faster inference, making it particularly suitable for real-time applications. [6] demonstrated that transformer-based models, when fine-tuned on domain-specific datasets, can achieve high accuracy in emotion classification tasks.

The GoEmotions dataset has become a benchmark resource in this area, providing 27 distinct emotion categories that enable fine-grained emotional classification. Its breadth and granularity make it especially relevant for analyzing complex emotional responses typical in interactive environments such as games. In this context, understanding player sentiment with greater specificity can inform adaptive systems that enhance engagement and immersion.

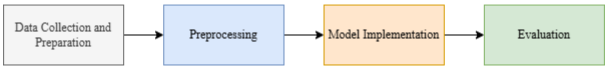
This study investigates the effectiveness of DistilBERT on the GoEmotions dataset for real-time sentiment analysis in game development. Sentiment analysis has become an increasingly valuable tool in interactive media, supporting features such as dynamic difficulty adjustment, emotion-sensitive NPC behavior, and adaptive narrative design. While earlier models like VADER offer computational simplicity, they lack the depth of contextual understanding required for nuanced emotional interpretation. Conversely, DistilBERT strikes a balance between accuracy and computational cost, positioning it as a viable model for integration into emotion-aware game systems.

By evaluating DistilBERT's performance on a complex, multi-label emotion dataset, this research contributes to the understanding of efficient transformer-based models in applied gaming contexts. The findings aim to assist developers in selecting sentiment analysis tools that align with both performance requirements and real-time constraints in modern game design.

III. RESEARCH METHODOLOGY

A. RESEARCH DESIGN

This research adopts a quantitative approach to build and evaluate a binary sentiment classification model ("Positive" vs. "Not Positive") for English-language text. The model used is DistilBERT for Sequence Classification, a lighter and faster variant of BERT designed to retain most of BERT's performance while reducing computational cost. The goal of this research is to assess the effectiveness of DistilBERT for sentiment analysis through data preprocessing, label re-mapping, model training, and performance evaluation using standard classification metrics.



Picture 1. Research Framework

B. DATASET: GoEmotions

1. Overview of the GoEmotions Dataset

The dataset used in this study is GoEmotions, developed by Google Research to support fine-grained emotion classification tasks. It consists of approximately 58,000 human-annotated English text samples, each tagged with one or more labels from a set of 27 distinct emotion categories. These categories span both basic emotions—such as joy, anger, sadness, fear, and surprise—as well as more nuanced emotions like pride, disgust, and embarrassment. Each text instance is typically a short phrase or sentence, making it highly relevant for applications involving brief user-generated content, such as chat messages or player feedback in games.

Originally intended for multi-label classification, the dataset provides a rich and diverse emotional landscape that captures the subtleties of human expression. For the purposes of this research, the 27 emotion labels have been simplified into binary sentiment classification task:

- **Positive**: Aggregated from joy, excitement, and pride.
- **Not positive**: Any samples not expressing these emotions are labeled as "Not Positive", including those with emotions like anger, annoyance, or sadness.

Metadata columns such as user ID, subreddit, and timestamps were removed during preprocessing. After label re-mapping and cleaning, the data was split into training and testing subsets with an 80:20 ratio.

Table 1. Dataset Sample Overview

Text	ID	Author	Subreddit	Admiration	Love	Pride	Sadness	Surprise
That game hurt.	eew5j0j	Brdd9	nrl	0	0	0	1	0
>sexuality shouldn't be a grouping category I...	eemcysk	TheGreen888	unpopularopinion	0	0	0	0	0
Man I love reddit.	eeibobj	MrsRobertshaw	facepalm	0	1	0	0	0
[NAME] was nowhere near them, he was by the Fanta...	eda6yn6	American_Fascist713	starwarsspeculation	0	0	0	0	0

2. Data Preprocessing

Before applying sentiment analysis models, the dataset needs to be preprocessed to ensure it is clean, standardized, and suitable for model training. The steps include:

- Text Cleaning
- Stop Word Removal
- Label Re-mapping

3. Feature Engineering

To prepare the data for the model, the 27 granular emotions were simplified into a binary classification task. The final labels were engineered by focusing exclusively on identifying positive sentiment.

The two final categories for the model are:

- **Positive (Label: 1):** This label is assigned to any text sample that expresses one or more of the core positive emotions: joy, excitement, or pride.
- **Not Positive (Label: 0):** This label is assigned to all other samples that do not contain the emotions above. This "catch-all" category includes texts with explicitly negative emotions (like anger, annoyance, sadness), neutral emotions, and any other emotion defined in the dataset.

This simplification of 27 granular emotions into a binary 'Positive' vs. 'Not Positive' model is a deliberate engineering choice. This process aligns with established emotion theories, such as Russell's Circumplex Model (1980), which posits that emotions can be fundamentally mapped to a dimension of valence (the positive vs. negative continuum). By focusing on this primary dimension, the model is trained to detect a clear and powerful emotional signal.

In the context of game development, this binary simplification allows for more manageable and actionable real-time player feedback. Games can respond directly to a 'Positive' or 'Not Positive' signal by modifying game mechanics, such as dynamic difficulty adjustment, NPC behavior, or narrative changes.

C. MODEL ARCHITECTURE

The sentiment analysis model is built using the DistilBertForSequenceClassification architecture from the Hugging Face Transformers library, implemented within a PyTorch framework. The entire process, from data preparation to evaluation, is designed to fine-tune this powerful yet efficient transformer model for the specific binary classification task. The choice of DistilBERT is strategic, prioritizing an optimal balance between high performance and computational efficiency. As a distilled version of BERT, it is approximately 60% faster and has 40% fewer parameters, which significantly reduces training time and memory requirements, all while retaining around 97% of the original model's language understanding capabilities. This makes DistilBERT a practical and effective choice for building a robust sentiment analysis pipeline without the significant computational overhead of larger transformer models [1].

IV. EXPERIMENT AND RESULT

This chapter presents a comprehensive evaluation of the DistilBERT model trained for binary sentiment classification. The analysis focuses on the model architecture, performance metrics, misclassification patterns, prediction confidence, and training stability to provide a thorough understanding of the model's capabilities and limitations.

A. MODEL ARCHITECTURE AND TRAINING SETUP

The model employed in this study is DistilBERT, a lighter and faster version of BERT (Bidirectional Encoder Representations from Transformers). The DistilBERT architecture retains approximately 97% of BERT's performance while being 60% faster and having 40% fewer parameters. Its architecture consists of:

- **6 Transformer Layers:** Each layer contains a multi-head self-attention mechanism and feed-forward networks, allowing the model to weigh the importance of different words in a sentence and understand context deeply.
- **Classification Head:** On top of the base DistilBERT layers, a dropout layer and a single linear (fully-connected) layer were added as the classification head. This head takes the output representation from DistilBERT and maps it to the two sentiment labels ("Not Positive" and "Positive").

The model was trained for 3 epochs using the AdamW optimizer with a learning rate of 2e-5.

B. PERFORMANCE EVALUATION

The model's performance was evaluated on both the training and test data. It is important to note that no separate validation set was used in this experiment. A validation set is typically used during training to monitor performance on unseen data and to detect overfitting early. Its absence is a limitation in this analysis.

1. Training and Test Performance

- Training Performance: Over 3 epochs, the accuracy on the training data increased from 93.2% to 94.3%.
- Test Performance: On the unseen test data, the overall accuracy achieved was 93%.
  This high accuracy is largely driven by the model's ability to classify the majority class. The classification report provides a more insightful, per-class performance breakdown.

2. Classification Report (Test Data)

Table 2. Sentiment Category Distribution

Class	Precision	Recall	F1-Score	Support
Not Positive	0.94	0.99	0.96	560
Positive	0.27	0.08	0.12	40

This report confirms the excellent performance on the "Not Positive" class but very poor performance on the minority "Positive" class, with a recall of just 0.08. This highlights the classic challenge of imbalanced classification.

3. Training Stability and Loss Analysis

The stability of the model's learning process was monitored via the training loss value. Although a loss curve was not explicitly plotted, the training progress bar indicated a consistent and healthy decrease in loss across each epoch:

- **Epoch 1:** Final Loss ≈ 0.277
- **Epoch 2:** Final Loss ≈ 0.216
- **Epoch 3:** Final Loss ≈ 0.165

This steady decrease suggests that the model was successfully learning from the data without signs of instability. However, without a validation loss curve to monitor alongside it, a definitive conclusion about overfitting cannot be made.

4. Discussion: DistilBERT vs. Traditional Embedding Models

While a direct empirical comparison with traditional embedding models (e.g., Word2Vec or GloVe with an SVM classifier) was not performed, it is important to discuss the theoretical advantages of using a Transformer-based model like DistilBERT.

Traditional embedding models often generate a single vector representation for each word, regardless of its context. In contrast, DistilBERT utilizes a self-attention mechanism. This allows it to dynamically weigh the relationship between all words in a text, resulting in context-sensitive embeddings. This means the word "bank" would have different representations in "river bank" and "investment bank." This ability to understand nuance, irony, and complex syntactical dependencies theoretically gives DistilBERT a significant advantage for complex language understanding tasks like sentiment analysis, which is expected to result in superior performance.

V. CONCLUSION AND FUTURE WORK

CONCLUSION

This research demonstrates the practical value of DistilBERT as a sentiment analysis model tailored for game development, achieving an accuracy of 93% on the GoEmotions dataset. DistilBERT's efficient architecture enables it to deliver high-quality emotion recognition while maintaining manageable computational demands, making it well-suited for integration into real-time game systems.

From a game design perspective, incorporating DistilBERT facilitates the creation of more emotionally responsive and adaptive gameplay. For instance, dynamic difficulty adjustment mechanisms can leverage nuanced emotion detection to tailor challenges according to player frustration or excitement levels. Similarly, NPCs can modify their behavior and dialogue in response to the player's affective state, fostering deeper immersion and a more personalized narrative experience.

Technically, DistilBERT's reduced model size and faster inference time allow for deployment in resource-constrained environments, such as mobile platforms or multiplayer games requiring low latency. This balance between speed and accuracy ensures that sentiment analysis can be performed without disrupting gameplay flow or increasing system load, a critical consideration for maintaining user engagement.

In summary, DistilBERT stands out as a versatile tool in the game developer's arsenal, enabling emotion-aware systems that enhance player experience through real-time adaptation. Its combination of contextual understanding and efficiency positions it as an optimal choice for modern games seeking to leverage the power of natural language processing to create more immersive, responsive, and player-centric environments.

Beyond model performance, this research underscores the transformative potential of integrating advanced sentiment analysis into game systems. Real-time emotion detection can enrich gameplay dynamics, enhance NPC responsiveness, and enable adaptive storytelling, ultimately fostering more immersive and personalized player experiences.

A. FUTURE WORK

The findings of this study open several promising avenues for future research, particularly in the domain of real-time sentiment analysis applications within game development:

A key direction for future work involves integrating DistilBERT-based sentiment analysis directly into live gameplay environments. By capturing player feedback through in-game text chat or voice transcripts, DistilBERT can enable dynamic gameplay adaptations. For example, emotionally aware NPCs could adjust their responses based on the player's detected mood—offering encouragement during frustration or increasing challenge levels when engagement or excitement is high. Similarly, narrative-driven games could personalize storylines in real-time, tailoring the experience to the player's emotional state. A frustrated player might receive assistance such as hints or difficulty reduction, whereas an excited player could unlock bonus content or additional challenges to sustain engagement.

Although this study centers on text-based sentiment analysis using DistilBERT, future research should explore multimodal emotion recognition, integrating voice, facial expression, and physiological data alongside text. Combining DistilBERT's text analysis with voice emotion recognition, for instance, could create more robust and nuanced emotional feedback systems. Such multimodal approaches would enable games to respond to player emotions more comprehensively, enhancing immersion and interaction quality. Techniques like speech-to-text combined with DistilBERT sentiment classification could further refine real-time emotional understanding across multiple communication channels.

Additional future work could focus on optimizing DistilBERT for deployment in real-time, resource-constrained environments, ensuring low latency without compromising accuracy. Moreover, fine-tuning DistilBERT on game-specific language and culture could improve its sensitivity to player context and slang, enhancing classification performance.

Overall, these directions aim to harness the capabilities of

DistilBERT to build emotionally intelligent, adaptive games that elevate player experience through responsive and personalized interactions.

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