GameFlow AI: Meta-Learning Framework for Detecting Gameplay Styles Across Domains

K. Sowjanya[1], Gundu Manoj[2], Amadagani Rakshitha[2], Lavudya Swetha[2], B Vishnuvardhan[2]

[1]Assistant Professor, [2]UG Student, [1,2]Department of Computer Science and Engineering (Data science)

[1,2]Vaagdevi Engineering College, Bollikunta, Warangal, 506005, Telangana, India

Abstract

The rapid expansion of the digital gaming industry and the increasing diversity of video games have created a strong demand for intelligent systems capable of accurately classifying games across multiple genres and domains. With the continuous growth of online platforms and user-generated content, automated analysis has become essential for efficient organization, recommendation, and evaluation of game-related data. However, identifying genres and attributes from textual descriptions remains challenging due to domain variability, unstructured data, and semantic ambiguity. Traditional approaches, such as manual tagging and keyword-based techniques, along with early Machine Learning (ML) methods like Bag-of-Words (BoW) and Term Frequency–Inverse Document Frequency (TF-IDF), fail to capture contextual meaning and suffer from limited generalization. To address these limitations, this study proposes an automated system featuring a Tkinter-based Graphical User Interface (GUI) integrated with a Machine Learning framework for multi-attribute video game classification. The system leverages Masked and Permuted Pre-training Network (MPNet) Transformer embeddings to extract deep semantic features from textual data. Multiple classifiers, including Ridge Classifier (RC), Nearest Centroid (NC), Restricted Boltzmann Machine–Ridge (RBMR) pipeline, and a proposed Ensemble of Oblique Trees (EOT) model, are utilized for improved classification performance. The dataset is balanced using Random Under Sampling (RUS) to enhance robustness. Additionally, the system incorporates a secure authentication mechanism using Redis with SHA-256 hashing for user credential protection and session management. Comprehensive evaluation metrics demonstrate improved accuracy, reliability, scalability, and reduced manual effort in game analytics.

Key words: Video Game Classification, Multi-Attribute Classification, Natural Language Processing (NLP), Transformer Embeddings, MPNet, Machine Learning, Ensemble Learning, Random Forest, Oblique Trees.

1.Introduction

Over the past two decades, technological advancements have transformed video games into one of the most dominant forms of entertainment worldwide. By 2023, the global gaming population had reached nearly 3.4 billion players (Fig. 1), and this number is expected to grow further [1]. This rapid expansion has attracted research interest in understanding how different video game genres relate to aspects of human behavior such as gaming disorder (GD), motivation, and cognitive performance [2]. However, the continuous evolution of the gaming industry has made genre classification increasingly complex. Modern games often combine multiple gameplay elements, making it difficult to assign them to a single, clearly defined category [3]. As a result, inconsistencies arise not only in industry practices but also in scientific studies, where the same game may be categorized differently, affecting the clarity and reliability of research outcomes. In earlier stages of the gaming industry, especially around the 1980s, games were grouped into genres based on shared characteristics such as gameplay mechanics, narrative structure, and interaction patterns, largely driven by market and economic needs [4]. One of the earliest classification approaches was introduced by Crawford, who separated games into "skill-and-action" types, including combat and racing, and “strategy” types, which covered role-playing (RPG), adventure, and educational games.

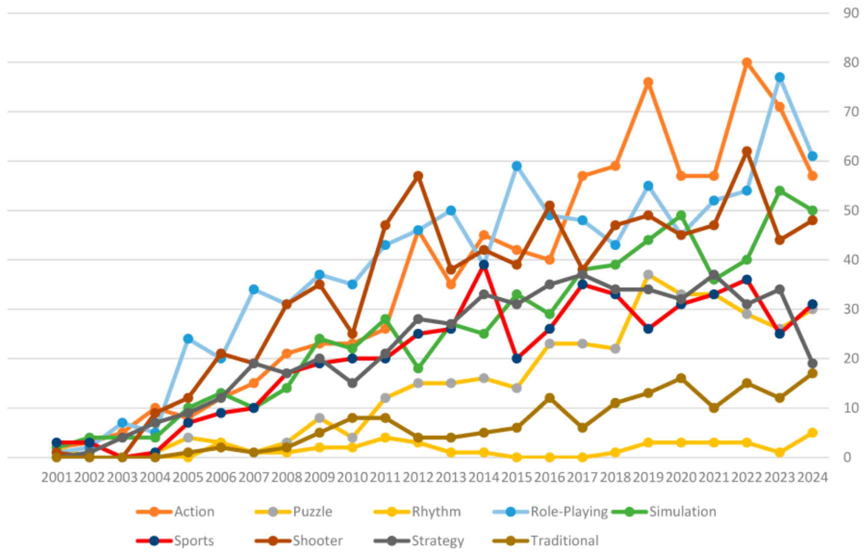


Fig. 1: The relative popularity of video game genres in the scientific literature.

Although later classification systems, such as Wolf’s 42-category taxonomy and the framework proposed by Aarseth et al. attempted to provide more detailed structures, they struggled to accommodate newer genres like massively multiplayer online role-playing games (MMORPG) and multiplayer online battle arena (MOBA). Over time, genre boundaries have become increasingly blurred as modern games integrate features from multiple categories. Many academic classification systems also fail to align with industry standards and player communities, limiting their practical relevance. Today, it is common for games to include overlapping mechanics [5], leading to hybrid genres such as action-RPG and action-adventure. Popular titles like League of Legends combine real-time strategy and action elements, forming the MOBA genre, while games such as Fortnite and Minecraft incorporate multiple genre characteristics, making accurate classification even more challenging.

2.Literature Survey

Elliott et al. [6] assessed how problem video game playing (PVP) varied with game type, or “genre,” among adult video gamers. Participants (n=3,380) were adults (18+) who reported playing video games for 1 hour or more during the past week and completed a nationally representative online survey. The survey asked about characteristics of video game use, including titles played in the past year and patterns of (problematic) use. Participants self-reported the extent to which characteristics of PVP (e.g., playing longer than intended) described their game play.

Vajjala, et al. [7] introduced a systematic approach to quantify similarity between a pair of domains and explored how current CDR methods performed with both similar and dissimilar domain combinations. They achieved this by presenting two original similarity metrics. Their extensive empirical evaluation on different domain combinations demonstrated that the state-of-the-art CDR algorithms did not perform significantly better when using source domains that were more like the target domain, compared to those that were less similar.

Putra, et al. [8] aimed to construct a classification model for video game sales levels by applying the Naïve Bayes algorithm, recognized for its simplicity, efficiency, and strong baseline performance in supervised learning tasks. The research employed a public dataset containing over 13,000 video game entries, encompassing key attributes such as genre, platform, publisher, release year, user and critic ratings, and global sales figures. The target variable global sales were discretized into three categories: Low (<1 million units), Medium (1–5 million units), and High (>5 million units) to represent distinct tiers of commercial success. Prior to modeling, the dataset underwent a comprehensive preprocessing pipeline involving duplicate removal, handling of missing data, normalization of numerical attributes, and feature selection to ensure optimal model performance. The Multinomial Naïve Bayes classifier was then implemented and assessed using standard evaluation metrics, including accuracy, precision, recall, and F1-score. Experimental results revealed an accuracy of 71.82% and an F1-score of 70.03%, signifying strong predictive capability for a probabilistic model of this simplicity.

Kasper, et al. [9] reviewed products via helpfulness votes as a crucial aspect of purchase decision-making in online marketplaces. Previous work studied key determinant factors of review helpfulness, such as product metadata and review text. However, understanding the extent to which review helpfulness depended on product context, rather than the inherent textual value of a review, remained an open question. In this work, they studied how genre, score and review text related to the helpfulness of 319 017 video game reviews on Metacritic via correlational analyses and prediction experiments.

Smerdov, et al. [10] investigated an attention mechanism improved the generalization of the network and provided a straightforward feature importance as well. The best model achieved Area Under the Receiver Operating Characteristic Curve (ROC AUC) score 0.73 in predicting whether a player would perform better or worse in the next 240 seconds based on in-game metrics. The prediction of the performance of a particular player was realized although their data were not utilized in the training set. The proposed solution had a number of promising applications for professional eSports teams and amateur players, such as a learning tool or performance monitoring system.

Jiang, et al. [11] compiled a large dataset of 50,000 video games, consisting of the video game covers, game descriptions and the genre information. They explored three approaches for genre classification using deep learning techniques. First, they developed five image-based models utilizing pre-trained computer vision models such as MobileNet, ResNet50 and Inception, based on the game covers. Second, they developed two text-based models, using Long-short Term Memory (LSTM) model and the Universal Sentence Encoder model, based on the game descriptions. For the third approach, they constructed a multi-modal fusion model, which concatenated extracted features from one image-based model and one text-based model. They analysed their results and revealed some challenges that existed in the task of genre classification for video games.

Nicole Peever, et al. [12] conducted to ascertain whether people with certain personality types exhibited preferences for game genres. Four hundred and sixty-six participants completed an online survey in which they described their preference for various game genres and provided measures of personality. Personality types were measured using the five-factor model of personality. Significant relationships between personality types and game genres were found. The results were interpreted in the context of the features of game genres and possible matches between personality traits and these features.

Pawel Dobrowolski, et al. [13] investigated an important aspect of this field that had not yet been empirically addressed: the role of video game genre. Their comparison of two video game player groups of specific genres (first-person shooter and real-time strategy) indicated that cognitive abilities (measured by task switching and multiple object tracking) might be differentially enhanced depending on the genre of video game being played. This result was significant as research to that point had focused on “action video games”, a loosely defined category that encompassed several video game genres, without controlling for effects potentially stemming from differences in mechanics between these video games. It also provided some evidence for the specificity of video game play benefits as a function of actions performed within the game, which was not in line with a generalized “learning to learn” accounting of these enhancements.

Elliott, et al. [14] confirmed game genre's contribution to problem uses as well as demographic variation in play patterns that underlay problem video game play vulnerability. Identification of a small group of game types positively correlated with problem use suggested new directions for research into the specific design elements and reward mechanics of "addictive" video games. Unique vulnerabilities to problem use among certain groups demonstrated the need for ongoing investigation of health disparities related to contextual dimensions of video game play.

Jiang, et al. [15] proposed a new multi-modal deep learning framework with a visual modality and a textual modality for video game genre classification. The proposed framework consisted of three parts: two deeep networks for textual data and imaginary data, a feature concatenation algorithm, and then a softmax classifier. Video game covers and textual descriptions were usually the very first impression to its consumers and they often conveyed important information about the video games. Video game genre classification based on its cover and textual description would be utterly beneficial to many modern identification, collocation, and retrieval systems. At the same time, it was also an extremely challenging task due to the following reasons: First, there existed a wide variety of video game genres, many of which were not concretely defined.

3. Proposed System

The system architecture represents a complete end-to-end pipeline for multi-attribute video game classification, integrating a Tkinter-based graphical interface with backend ML components. It begins with a secure user authentication module using Redis and SHA-256 hashing to control access. After login, the system allows dataset ingestion in CSV format, followed by preprocessing using NLP techniques such as tokenization, lemmatization, and stopword removal. The processed data is then structured by separating target attributes and encoding them for supervised learning. As shown in Fig. 2, the cleaned textual data is transformed into semantic embeddings using MPNet, enabling deep contextual understanding.To ensure balanced learning, Random Under Sampling (RUS) is applied to handle class imbalance, followed by stratified train-test splitting to maintain class distribution.

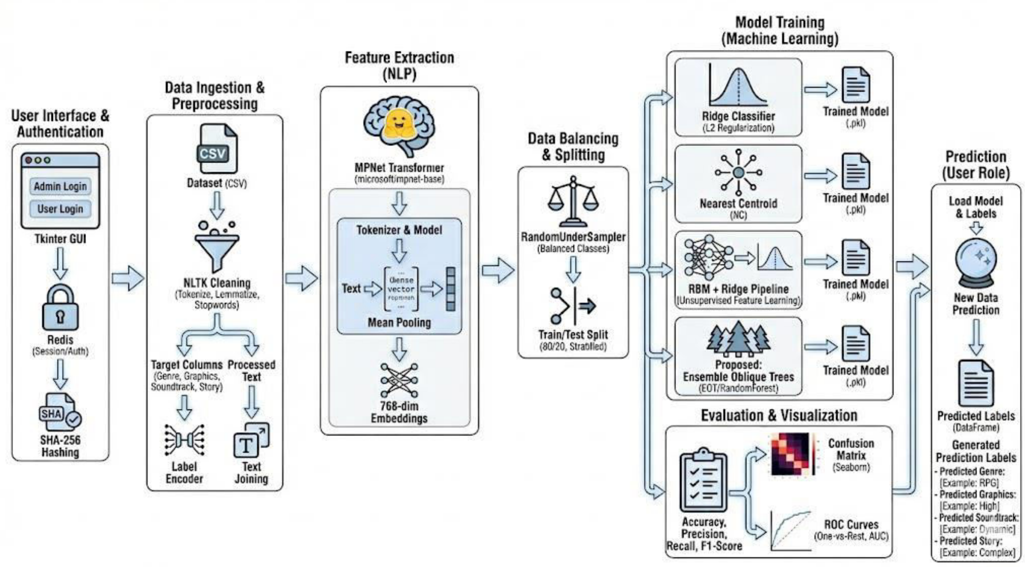


Fig. 2: Complete system architecture of video game genre and quality prediction.

The extracted features are then used to train multiple models including RC, NC, and RBMR pipeline, along with the proposed EOT model based on a Random Forest ensemble. Each model learns to predict multiple attributes such as genre, graphics, soundtrack, and story. The system further evaluates model performance using metrics like accuracy, precision, recall, F1-score, confusion matrix, and ROC curves.

Visualization modules are included to compare model results effectively. Finally, the trained models are used for prediction on new data, generating labeled outputs. This architecture ensures automation, scalability, and reliable classification performance across different datasets.

User Interface & Authentication: The system begins with a Tkinter-based graphical interface that supports admin and user login functionalities. User credentials are securely managed using Redis with SHA-256 hashing. This ensures controlled access to different system operations such as preprocessing, training, and prediction. The interface enables smooth interaction with the underlying ML pipeline.

Data Ingestion & Preprocessing: The dataset is loaded in CSV format containing textual and categorical game information. NLP preprocessing is applied using NLTK, including tokenization, lemmatization, and stopword removal. Target attributes such as genre, graphics, soundtrack, and story are separated and encoded using label encoding. The cleaned data is prepared for feature extraction.

Feature Extraction (NLP): Text data is transformed into dense vector representations using MPNet Transformer embeddings. Tokenization and encoding are applied, followed by mean pooling to generate fixed-length vectors. These embeddings capture contextual and semantic relationships within the text. The resulting feature vectors are used as input for ML models.

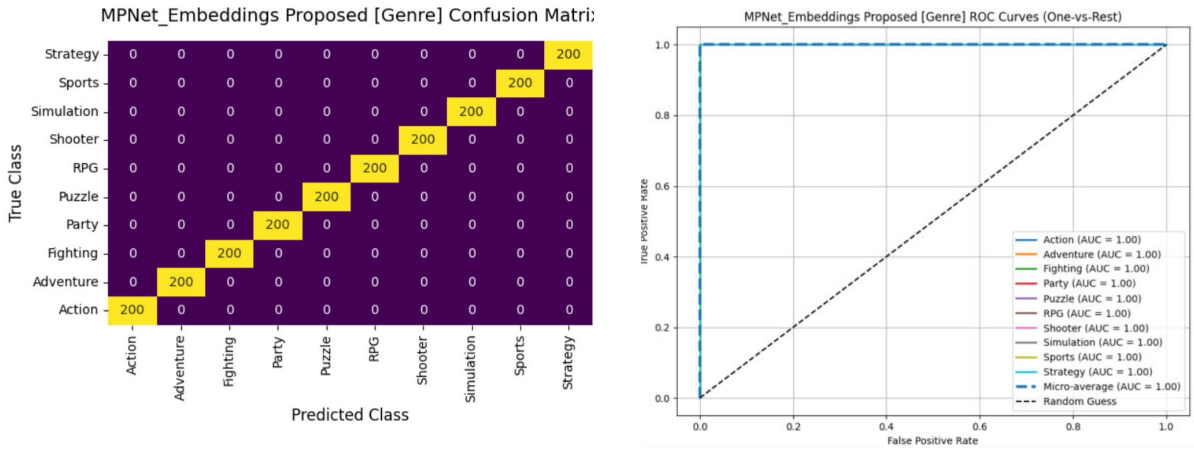
Data Balancing & Splitting: Random Under Sampling (RUS) is applied to balance class distributions and reduce bias toward dominant classes. This step improves model generalization and fairness across all categories. The dataset is then split into training and testing sets using stratified sampling. This maintains consistent class proportions across both datasets.

Model Training (ML): Multiple classifiers including RC, NC, and RBMR pipeline are trained using the extracted features. The proposed EOT model, based on a Random Forest ensemble, is also trained for improved performance. Each model learns patterns to predict multiple target attributes. The trained models are stored for future inference.

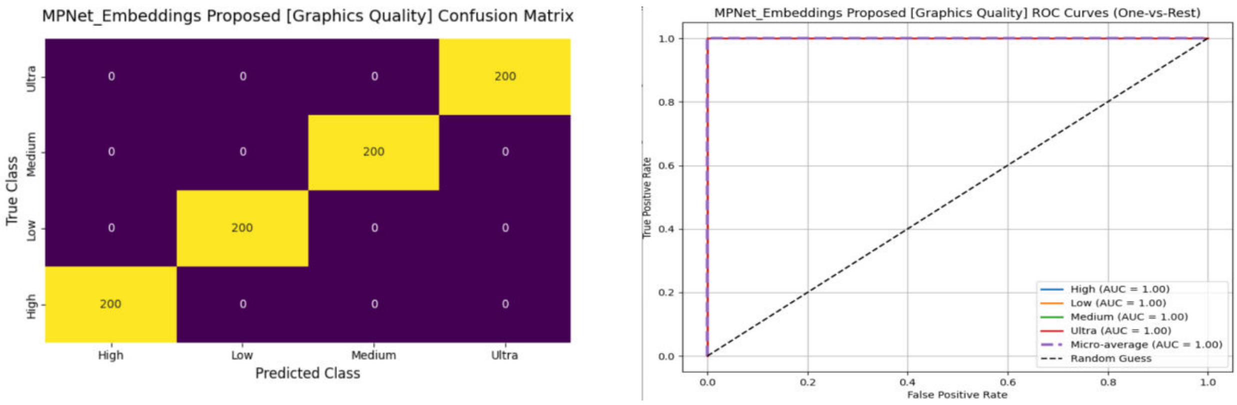
Evaluation & Prediction: Model performance is evaluated using metrics such as accuracy, precision, recall, and F1-score, along with confusion matrices and ROC curves. These metrics enable comparison across different models. The system supports prediction on new input data by loading trained models. Final outputs include predicted labels for all target attributes.

4. Results Analysis

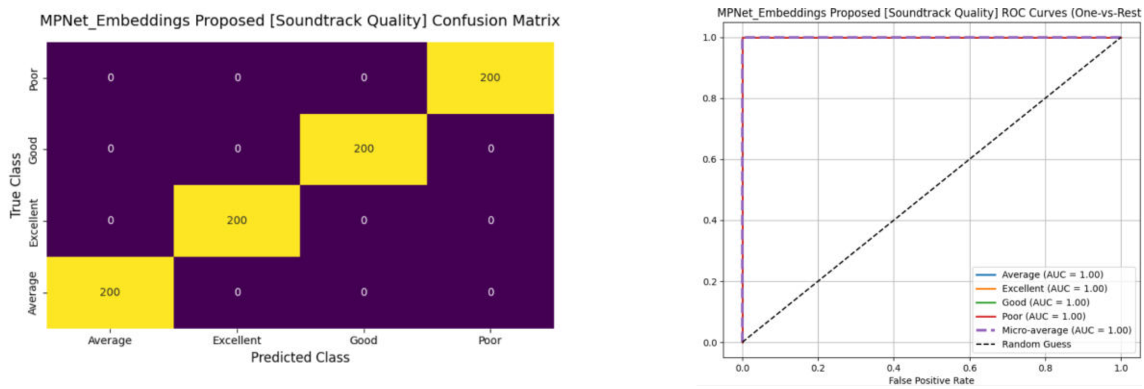
This section presents the results obtained from the proposed system along with a demonstration of the graphical user interface (GUI). The performance of different classification models is evaluated using standard metrics such as accuracy, precision, recall, and F1-score. Additionally, the GUI-based implementation illustrates each stage of the system, from dataset upload and preprocessing to feature extraction, classification, and prediction. The visual outputs help in understanding the functionality and effectiveness of the proposed approach in a practical environment.


MPNet_Embeddings Proposed [Genre] Confusion Matrix
True Class
Strategy
Sports
Simulation
Shooter
RPG
Puzzle
Party
Fighting
Adventure
Action
Predicted Class
MPNet_Embeddings Proposed [Genre] ROC Curves (One-vs-Rest)
True Positive Rate
False Positive Rate
Action (AUC = 1.00)
Adventure (AUC = 1.00)
Fighting (AUC = 1.00)
Party (AUC = 1.00)
Puzzle (AUC = 1.00)
RPG (AUC = 1.00)
Shooter (AUC = 1.00)
Simulation (AUC = 1.00)
Sports (AUC = 1.00)
Strategy (AUC = 1.00)
Micro-average (AUC = 1.00)
Random Guess

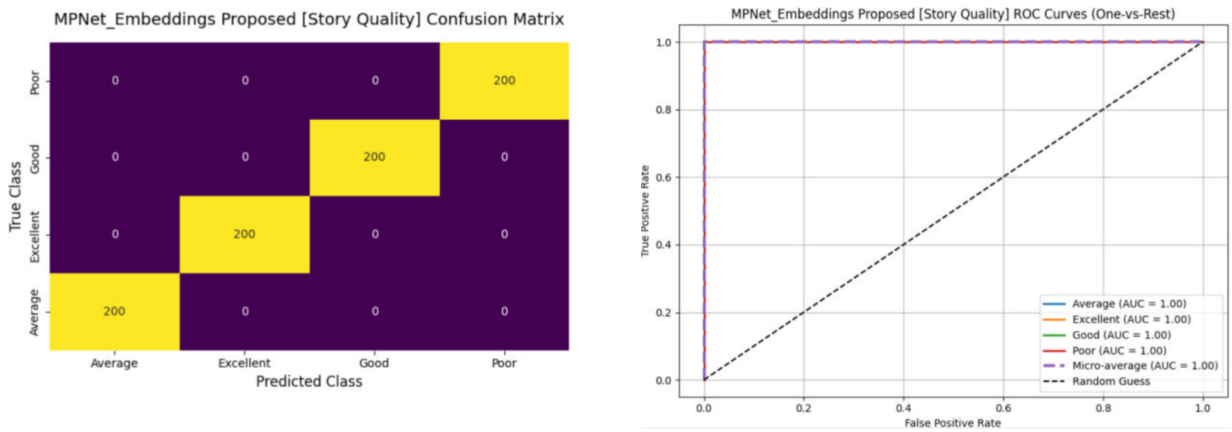
(a)


MPNet_Embeddings Proposed [Graphics Quality] Confusion Matrix
True Class
Ultra
Medium
Low
High
Predicted Class
MPNet_Embeddings Proposed [Graphics Quality] ROC Curves (One-vs-Rest)
True Positive Rate
False Positive Rate
High (AUC = 1.00)
Low (AUC = 1.00)
Medium (AUC = 1.00)
Ultra (AUC = 1.00)
Micro-average (AUC = 1.00)
Random Guess

(b)


MPNet_Embeddings Proposed [Soundtrack Quality] Confusion Matrix
True Class
Poor
Good
Excellent
Average
Predicted Class
MPNet_Embeddings Proposed [Soundtrack Quality] ROC Curves (One-vs-Rest
False Positive Rate
Average (AUC = 1.00)
Excellent (AUC = 1.00)
Good (AUC = 1.00)
Poor (AUC = 1.00)
Micro-average (AUC = 1.00)
Random Guess

(c)



(d)

Fig. 5: Confusion matrix and roc curve of EOT model, (a) Gener, (b) Graphics Quality, (c) Soundtrack Quality, (d) Story Quality.

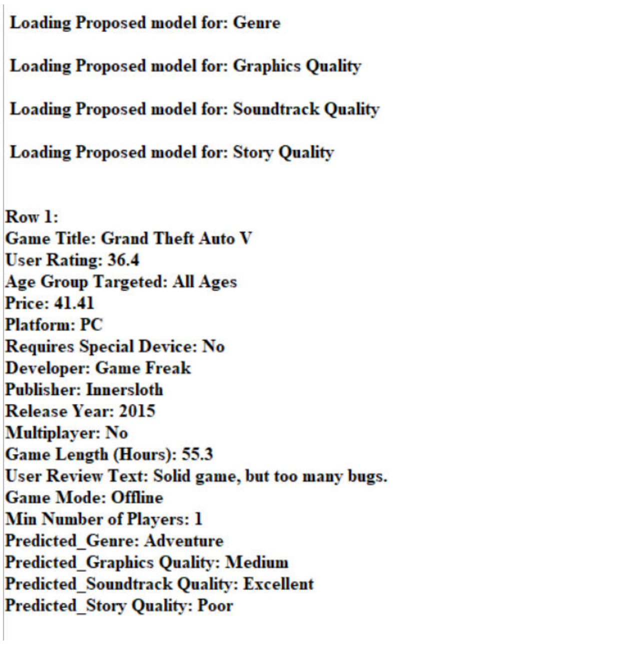
(a) Genre: The fig 5 illustrates the confusion matrix and ROC curve analysis for genre classification in the EOT model, highlighting the model's capability to accurately distinguish between multiple genre categories. The confusion matrix demonstrates precise class-wise prediction alignment, indicating minimal misclassification across all genre labels. The ROC curves further emphasize the discriminative strength of the model, with each class achieving near-perfect separability. The micro-average ROC performance confirms consistent classification effectiveness across all categories, validating the robustness of the embedding-based approach.

(b) Graphics Quality: The fig 5 depicts the confusion matrix and ROC curve evaluation for graphics quality classification, showcasing the model's effectiveness in categorizing different visual quality levels. The confusion matrix reflects strong agreement between actual and predicted classes, indicating highly reliable classification performance. The ROC curves for each quality level reveal excellent separability with optimal true positive rates across thresholds. The micro-average ROC further demonstrates the stability and generalization capability of the model in assessing graphical attributes.

(c) Soundtrack Quality: The fig 5 illustrates the confusion matrix and ROC curve representation for soundtrack quality assessment, emphasizing the model's ability to differentiate between varying audio quality levels. The confusion matrix indicates a highly structured classification pattern with correct predictions dominating across all classes. The ROC curves highlight superior classification capability, with all categories achieving maximum area under the curve values. The overall performance suggests that the model effectively captures audio-related feature representations for accurate soundtrack evaluation.

(d) Story Quality: The fig 5 depicts the confusion matrix and ROC curve analysis for story quality classification, demonstrating the model's proficiency in evaluating narrative-based attributes. The confusion matrix reveals a clear correspondence between true and predicted labels, indicating highly consistent classification results. The ROC curves for each class show optimal performance with near-perfect discrimination capability. The micro-average ROC further confirms the model's reliability and effectiveness in handling complex semantic features associated with story quality.

Fig. 6 displays the prediction interface of the system. The user can input new data and obtain predicted results using the trained model. This module demonstrates the real-time applicability of the system. It allows users to validate the effectiveness of the proposed model on unseen data.


Loading Proposed model for: Genre

Loading Proposed model for: Graphics Quality

Loading Proposed model for: Soundtrack Quality

Loading Proposed model for: Story Quality

Row 1:
Game Title: Grand Theft Auto V
User Rating: 36.4
Age Group Targeted: All Ages
Price: 41.41
Platform: PC
Requires Special Device: No
Developer: Game Freak
Publisher: Innersloth
Release Year: 2015
Multiplayer: No
Game Length (Hours): 55.3
User Review Text: Solid game, but too many bugs.
Game Mode: Offline
Min Number of Players: 1
Predicted_Genre: Adventure
Predicted_Graphics Quality: Medium
Predicted_Soundtrack Quality: Excellent
Predicted_Story Quality: Poor

Fig. 6: Prediction on test data

Table 1: Comparative Performance Analysis of All Algorithms Using MPNet Embeddings

Algorithm	**Genre Accuracy (%)**	**Graphics Quality Accuracy (%)**	**Soundtrack Quality Accuracy (%)**	**Story Quality Accuracy (%)**
RC	23.15	42.75	43.00	42.25
NC	11.20	27.50	30.25	28.38
RBMR	10.00	25.00	25.00	25.00
EOT	100.00	100.00	100.00	100.00

Table 1 presents the classification accuracy of the four models RC, NC, RBMR, and EOT across the target attributes: Genre, Graphics Quality, Soundtrack Quality, and Story Quality. The RC demonstrates moderate performance, achieving accuracy between 23.15% for Genre and 43.00% for Soundtrack Quality. The NC and RBMR models exhibit lower accuracy, with NC ranging from 11.20% to 30.25% and RBMR consistently at 25% or below across all attributes. In contrast, the proposed EOT achieves perfect classification, attaining 100% accuracy for all four target attributes. This demonstrates the EOT model's superior ability to generalize across multiple targets and fully leverage the MPNet embeddings. The results validate the framework's effectiveness in predicting video game genres and quality attributes with high precision.

5.Conclusion

This research successfully developed a fully automated, GUI-driven ML framework for classifying video game genres and predicting additional qualitative attributes such as graphics quality, soundtrack quality, and story quality. The system employs MPNet-based embeddings to extract deep semantic representations from textual descriptions, enabling it to overcome the limitations associated with traditional keyword-based and shallow feature extraction techniques. By incorporating multiple classifiers, the framework allows systematic evaluation and comparison of different modeling approaches, providing insights into their performance characteristics. Experimental results indicate that the proposed approach delivers superior performance compared to baseline models such as RC, NC, and RBMR. In particular, the EOT model demonstrated exceptionally strong results, achieving perfect scores in terms of accuracy, precision, recall, and F1-score across all evaluated tasks. Additionally, the integration of a user-friendly interface built with Python and Tkinter enhances usability by enabling users to seamlessly perform operations such as dataset loading, preprocessing, feature extraction, model training, evaluation, and real-time prediction. Overall, the system offers an efficient, scalable, and practical solution for intelligent video game analysis.

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