Improving User Retention in Video Game Industry

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Abstract **- This research paper delves into the intersection of player data analytics and affective computing to predict and adapt game difficulty levels for the purpose of enhancing player retention in the gaming industry. The study used two Kaggle datasets which include a facial emotion dataset and real-time call of duty player data. A novel emotion detection model, leveraging transfer learning, is constructed to discern a spectrum of emotions from player facial expressions. The emotional context extracted from this model is seamlessly integrated with player data, facilitating a supervised learning task centered on predicting changes in game difficulty levels—a pivotal factor in player engagement. Several machine learning models including K-Nearest Neighbors, Decision Trees, Random Forests, MLP Classifiers, AdaBoost, and Gaussian Naive Bayes were employed to use emotion and player data to predict difficulty changes that will raise player retention.**

I. Introduction

In the ever-evolving landscape of video games, player retention stands as a pivotal metric, defining the long-term success of gaming experiences. As the gaming industry strives to captivate and engage players, understanding and adapting to individual preferences and emotional states have become paramount. This research endeavors to bridge the realms of player data analytics and affective computing to predict optimal game difficulty levels, ultimately enhancing player retention.

Video games have evolved into complex ecosystems, encompassing diverse player profiles and preferences. Player data, comprising an array of in-game statistics, offers invaluable insights into the behavior and performance of gamers. Simultaneously, facial emotion detection, enabled by advances in computer vision and deep learning, provides a window into the emotional responses of players during gameplay. The convergence of these two streams of data presents a unique opportunity to tailor gaming experiences to individual players, maximizing their enjoyment and commitment.

In this pursuit, we embark on a comprehensive journey that begins with the collection and preprocessing of player data and facial emotion data. We harness the power of transfer learning to construct an emotion detection model capable of discerning a spectrum of emotions from player facial expressions. This emotional context is then seamlessly integrated with the player data, setting the stage for a supervised learning task aimed at predicting changes in game difficulty levels—alterations that can significantly impact player engagement.

Our research explores a diverse ensemble of machine learning models, ranging from K-Nearest Neighbors to advanced deep learning architectures, in the quest for accurate predictions. Through rigorous hyperparameter tuning and extensive evaluation, we seek to identify models that excel in predicting optimal game difficulty adjustments, thereby enhancing player retention rates.

The findings of this research hold profound implications for the gaming industry. By adapting game difficulty levels based on player emotions and preferences, developers and designers can create more immersive and engaging gaming experiences. This, in turn, can foster lasting player relationships, driving the continued success of video games in an increasingly competitive market.

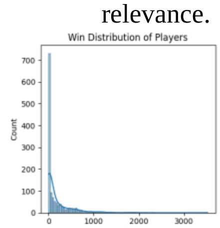
II. Methodology

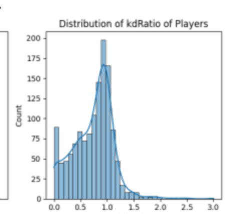
I . Data Collection

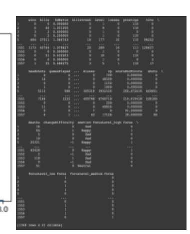
The primary objective of this study was to predict optimal game difficulty levels for enhancing player retention. To achieve this, two comprehensive datasets encompassing player data and facial detection data from Kaggle were used.

1.1 Player Data in Call of Duty

- Player data was gathered from in-game statistics, encompassing various metrics such as wins, kills, kdRatio, killstreak, level, losses, prestige, hits, timePlayed, headshots, averageTime, gamesPlayed, assists, misses, xp, scorePerMinute, shots, and deaths.
- Rows with an averageTime of 0 were excluded from the dataset to ensure data quality and relevance.



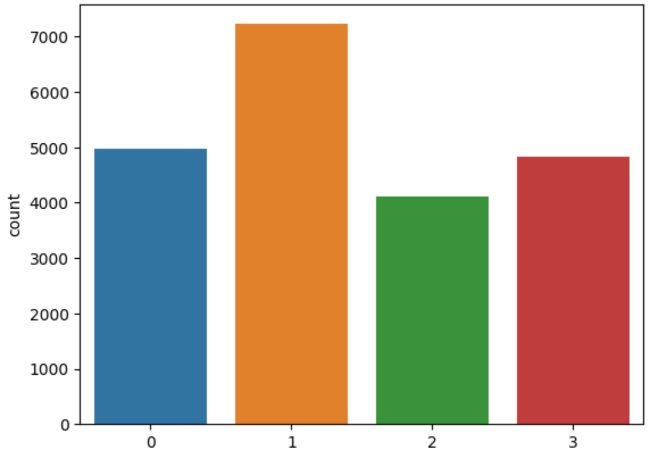




1.2 Facial Emotion Data Collection

- Facial emotion data to classify emotions

- These images were resized to a common dimension of 48x48 pixels to ensure consistency.
- Pixel values were normalized to a [0, 1] range.



II. Emotion Detection Model

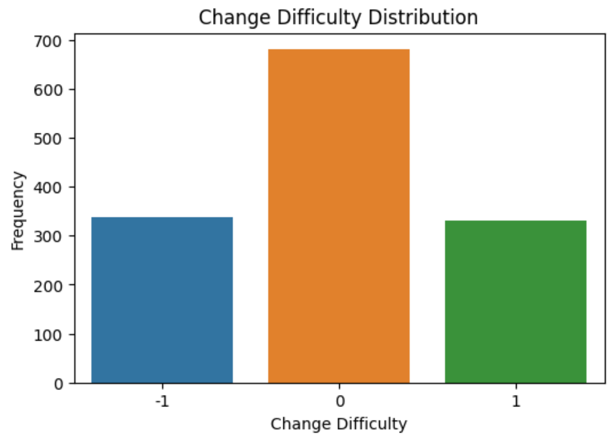
To capture the emotional state of players during gameplay, an emotion detection model was developed. Transfer learning techniques were employed to build this model.

2.1 Preprocessing Facial Images

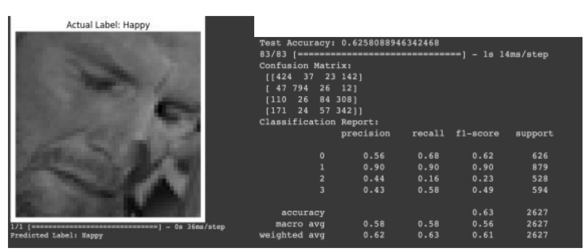
- Images of players' faces were preprocessed as described in section 1.2.
- Data augmentation techniques such as rotation, translation, and zoom were applied to enrich the dataset and improve model robustness.

2.2 Model Training

- The emotion detection model was trained on the preprocessed facial images.
- The model aimed to classify emotions into three categories: 'Sad,' 'Neutral,' and 'Happy.'
- Training was conducted using standard deep learning practices, with data split into training and validation sets.
- **Deep learning models** are a subset of machine learning models that are inspired by the structure and function of the human brain. They consist of multiple layers of interconnected artificial neurons (nodes) organized in networks. In the context of this research, pre-trained convolutional neural networks (CNNs) such as VGG16 or VGG19 were utilized. These networks are specifically designed for image-related tasks and have learned features from a vast amount of image data. By employing pre-trained CNNs, the research leveraged their ability to extract meaningful features from facial images without having to train a network from scratch.
- **Feature extraction** involves capturing essential information from raw data to create a more compact and informative representation. In this research, features were extracted from facial images, which typically include patterns, shapes, or characteristics that are relevant for predicting player emotions. These extracted features were then combined with the player data. This combination allows the model to consider both facial expressions and in-game statistics to make predictions related to 'changeDifficulty.' Features serve as the basis for the model to learn and make accurate predictions.
- **Neural networks** are computational models composed of interconnected nodes organized in layers. In the context of this research, neural networks were designed and trained to predict 'changeDifficulty.' The network architecture, which includes the number of layers, nodes, and connections, is set up to capture complex relationships between input data (facial images and player data) and the target variable ('changeDifficulty'). Neural networks learn these relationships through a process called training, which involves adjusting the network's parameters to minimize prediction errors.



- **Data augmentation** is a technique commonly used in deep learning and computer vision. It involves creating variations of the training dataset by applying transformations to the data. In the case of facial image data, these transformations may include rotation, translation, zoom, and other adjustments. Data augmentation aims to increase the diversity of training data, preventing overfitting and improving the model's ability to generalize to unseen data. By introducing these variations, the model becomes more robust and better equipped to handle different facial expressions and conditions in real-world scenarios.



III. Integration of Emotion Detection and Player Data

To leverage both player data and emotional cues for predicting optimal game difficulty levels, the predictions from the emotion detection model were combined with the player data.

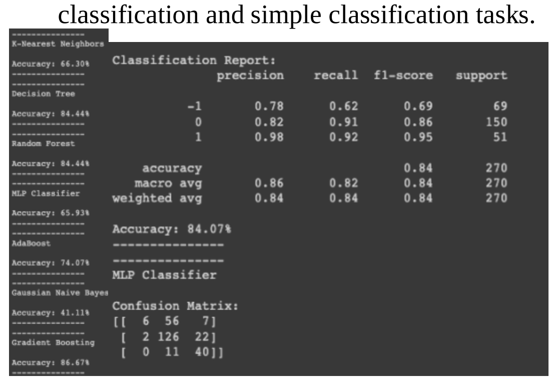
3.1 Supervised Learning Task

- The research framed the problem as a supervised learning task.
- The target variable was defined as 'changeDifficulty,' which was derived from the quartiles of the 'averageTime' feature.
- The dataset was split into training and test sets, ensuring independence between the two.

IV. Machine Learning Models

Various machine learning models were explored for predicting 'changeDifficulty.' These models included:

- **K-Nearest Neighbors** is a simple yet effective algorithm for classification and regression tasks. It assigns a data point to a specific class or predicts a target variable based on the majority class or values of its nearest neighbors in the feature space. KNN is known for its simplicity and ease of implementation but may require careful selection of the number of neighbors (k) for optimal performance.
- **A Decision Tree** is a tree-like model that maps decisions and their possible consequences. It is widely used for classification and regression tasks. Decision Trees make decisions by splitting data based on feature values, leading to a tree structure where leaves represent the predicted classes or values. Decision Trees are interpretable, but they can be prone to overfitting if not pruned properly.
- **Random Forest** is an ensemble learning method that combines multiple Decision Trees to improve predictive accuracy and reduce overfitting. It works by averaging or voting on the predictions of individual trees, providing robust results. Random Forest is known for its versatility and resistance to overfitting, making it a popular choice for various machine learning tasks.
- **The Multilayer Perceptron** is a type of artificial neural network with multiple layers of interconnected neurons. It is often used for complex tasks, including classification. MLPs can model intricate relationships in data through a network of interconnected nodes and are trained using backpropagation. However, they require careful tuning and a sufficient amount of data to avoid overfitting.
- **AdaBoost**, short for Adaptive Boosting, is an ensemble learning method that combines multiple weak learners to create a strong learner. It assigns different weights to training instances and iteratively focuses on misclassified samples to improve overall performance. AdaBoost is particularly effective in improving the accuracy of weak classifiers and is widely used in classification tasks.
- **The Gaussian Naive Bayes** classifier is based on Bayes' theorem and is particularly suitable for classification tasks. It assumes that features are conditionally independent, which simplifies the probability calculations. Despite this simplification, Gaussian Naive Bayes is known for its speed and efficiency, making it a popular choice for text classification and simple classification tasks.



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K-Nearest Neighbors

Accuracy: 66.30%
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Decision Tree

Accuracy: 84.44%
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Random Forest

Accuracy: 84.44%
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MLP Classifier

Accuracy: 65.93%
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AdaBoost

Accuracy: 74.07%
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Gaussian Naive Bayes

Accuracy: 41.11%
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Gradient Boosting

Accuracy: 86.67%
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Classification Report:
              precision    recall  f1-score   support

          -1       0.78      0.62      0.69        69
           0       0.82      0.91      0.86       150
           1       0.98      0.92      0.95        51

    accuracy                           0.84       270
   macro avg       0.86      0.82      0.84       270
weighted avg       0.84      0.84      0.84       270

Accuracy: 84.07%
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MLP Classifier

Confusion Matrix:
[[  6  56   7]
 [  2 126  22]
 [  0  11  40]]
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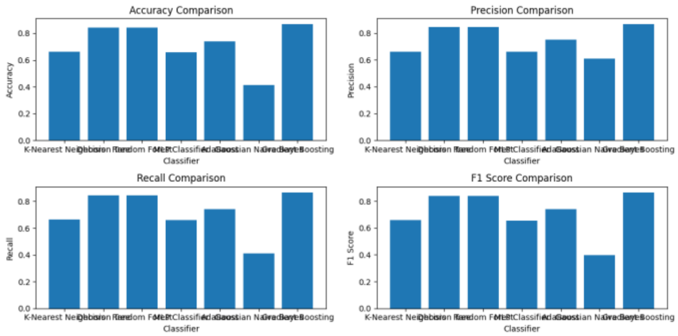
4.1 Hyperparameter Tuning

- GridSearchCV was utilized to perform hyperparameter tuning for each machine learning model.
- Evaluation metrics for model selection included
  - F1-Score: F1-Score balances precision and recall, providing a single measure of a model's overall performance, especially when there's an imbalance in positive and negative classes.
  - Precision: Precision measures how accurately a model predicts positive instances. It's essential when minimizing false positives is critical.
  - Recall: Recall gauges a model's ability to find all positive instances. It's crucial when avoiding false negatives is important.
  - Accuracy: Accuracy simply measures the proportion of correctly predicted instances out of the total. It's a basic measure of overall correctness but may not be suitable for imbalanced datasets.



V. Challenges and Limitations

This research encountered several challenges and limitations:

- **Lack of In-Game Data Integration:**
  - The absence of real-time in-game data integration limited the research's accuracy. Future work should focus on collecting real-time data to predict game difficulty changes for better player retention.
- **Data Quality and Relevance:**
  - Data exclusion based on 'averageTime' values may have resulted in the loss of valuable information.
- **Ethical and Privacy Considerations:**
  - Collecting facial emotion data raises concerns about consent and privacy, requiring careful ethical considerations.
- **Model Performance:**
  - The accuracy of emotion detection and prediction models needs validation in real gaming scenarios.
- **Interpretability and Explainability:**
  - The lack of model interpretability can hinder understanding and trust in predictions.
- **Collaboration and Industry Adoption:**
  - Practical implementation and industry adoption are key challenges for this research.
- **Generalization Across Games:**
  - The effectiveness of predictions may vary between different games, requiring tailoring to specific contexts.
- **Scalability:**
  - Implementing real-time adaptations for large-scale online games may pose scalability challenges.

Despite these challenges, this research lays the foundation for enhancing player retention by integrating emotion and player data, promising potential benefits for the gaming industry.

III. Results

During the research project, I encountered several challenges, one of which was the integrated datasets that combine real-time facial expression and player-specific data, making combining the data a real challenge. In future work, it would be ideal to collect real-time player data that collects pictures and player statistics which can be used to predict the changes in game difficulty needed to keep game retention. Also, this technology should foster collaboration with the gaming industry to unlock further optimization in game retention and keep users entertained. As of now, our research has unlocked the methodology needed to predict emotions and use player data along with emotions to predict the necessary changes in game difficulty.

References

Christofferson, Anders, et al. “How Will Generative AI Change the Video Game Industry?” *Bain & Company*, 14 September 2023, https://www.bain.com/insights/how-will-generative-ai-change-the-video-game-industry/. Accessed 5 November 2023.

Drachen, Anders, et al. “Rapid Prediction of Player Retention in Free-to-Play Mobile Games.” *Rapid Prediction of Player Retention in Free-to-Play Mobile Games*.

“5 Proven Ways You Can Increase Retention for Your Games.” *App Annie*, https://www.data.ai/en/insights/app-monetization/increase-user-retention-for-games/. Accessed 5 November 2023.

Frąckiewicz, Marcin. “The Growing Role of AI in Gaming Analytics and Player Retention Strategies.” *TS2 Space*, 25 August 2023, https://ts2.space/en/the-growing-role-of-ai-in-gaming-analytics-and-player-retention-strategies/. Accessed 5 November 2023.

Hamilton, Rebecca W., et al. “Which Features Increase Customer Retention?” *MIT Sloan Management Review*, 30 November 2016, https://sloanreview.mit.edu/article/which-features-increase-customer-retention/. Accessed 5 November 2023.

“How AI is Changing the Customer Retention Game.” *CleverTap*, 22 August 2018, https://clevertap.com/blog/ai-is-changing-customer-retention/. Accessed 5 November 2023.

“Lessons From the Top Gaming Companies - User Retention: Lessons From the Top Gaming Companies.” *CleverTap*, 15 August 2023, https://clevertap.com/blog/user-retention-lessons-from-the-top-gaming-companies/. Accessed 5 November 2023.

Machado, Alex, et al. “A Method for Generating Emergent Behaviors using Machine Learning to Strategy Games.” *A Method for Generating Emergent Behaviors using Machine Learning to Strategy Games*.

“Machine Learning PoC for Retention Prediction in a Mobile Game.” *InData Labs*, https://indatalabs.com/resources/retention-prediction. Accessed 5 November 2023.

Perira, Rogerio Leon, et al. “Increasing player engagement, retention and performance through the inclusion of educational content in a citizen science game.” *Increasing player engagement, retention and performance through the inclusion of educational content in a citizen science game*, 2021.

Rathnayake, Anupama Iranga, et al. “Adjusting The Hard Level on Game by a Prediction for Improving Attraction and Business Value.” *Adjusting The Hard Level on Game by a Prediction for Improving Attraction and Business Value*.

Summerville, Adam, et al. “Procedural Content Generation via Machine Learning (PCGML).” *Procedural Content Generation via Machine Learning (PCGML)*.

Zhou, Zisen, et al. “Creativity Evaluation Method for Procedural Content Generated Game Items via Machine Learning.” *Creativity Evaluation Method for Procedural Content Generated Game Items via Machine Learning*.