# Leveraging Convolutional Neural Networks for Evaluating Horror Games: A Novel Approach for Capturing Player Experience and Feedback

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## Abstract:

Horror games stand out as one of the most viscerally immersive forms of content in the rapidly evolving space of interactive entertainment. Understanding and improving the horror game player experience therefore requires a methodical approach and employs metrics that can characterise the harnessing of various emotions and perturbations elicited by these titles. Traditional assessment approaches often rely on qualitative measures that are often highly subjective and hard to quantify. In this paper, we present a new method to assess horror games using real-time player reaction analysis with convolutional neural networks (CNNs). We introduce a model that utilises Convolutional Neural Networks (CNNs) to analyse in-game behaviour, physiological data and facial expressions to quantify experience with minimal bias. We train our model on biometric data derived from instances of gameplay sessions and from offline video-clips of people's faces as they play games. By correlating these metrics with specific in-game events captured by game engines, our technology can detect trends and predict levels of fright, worrying or engagement. We found that CNNs perform with high accuracy at recognising and categorising emotions, offering an instrument to improve the work of horror game developers. Moreover, our approach can be scaled to improve the player experience for other gaming genres with similar data-driven recommendations. This research will ultimately enable better, more sophisticated and more flexible game production methods for the creation of games that will draw us closer to fictional experiences and are more remarkable than many of the games that are currently available.

## Keywords

Horror games, player experience, Convolutional Neural Networks, emotional response, biometric data, game design, immersive experience.

## Introduction

Horror games are a special case within the games industry in part because they rely on emotional experiences – such as fear, anxiety and suspense – in a particularly powerful way. Such experiences are key to making gameplay environments feel immersive and engaging to players. These emotional experiences are also particularly difficult to measure because they have to deal with highly subjective player feedback, which can vary and be imperfectly documented [1].

Convolutional Neural Networks (CNNs), one of the most recent developments in machine learning, have shown great promise in evaluating emotional reactions objectively. CNNs' strong pattern recognition abilities have allowed them to be used successfully in a variety of image and video analysis applications [2]. The game business can greatly benefit from their potential in emotion recognition through the study of biometric data and facial expressions [3]. In order to assess participant reports in horror video games, this take a look at gives a unique framework that makes use of CNNs to investigate actual-time records, which include in-recreation behavior, physiological reactions, and facial expressions.

the sentimental country or infer gender. Because each assignment's samples vary greatly, applying machine learning (ML) techniques to effectively interpret any of these components has proven to be difficult. the human accuracy for classifying an picture of a face in one in all 7 special feelings is 65%±5% [8]. One can look at the difficulty of this assignment through attempting to manually classify the kaggle facial expression data set pictures in Fig 1 inside the following training ["angry", "disgust", "fear", "happy", "neutral", "sad", "surprise"].

Fig. 1: sample kaggle facial expression data set

Previous research have emphasised the significance of physiological signs in representing players' emotional states at some stage in gameplay, such as coronary heart price, galvanic pores and skin reaction, and facial expressions [4, 5]. Our approach seeks to provide an goal and quantitative evaluation of player enjoy by way of the usage of CNNs to technique and correlate these statistics with positive in-recreation occurrences.

Furthermore, the integration of CNNs on this context is supported by way of the growing frame of studies that explores the application of deep gaining knowledge of strategies in emotion detection and user revel in evaluation [6, 7]. This paper now not best seeks to validate the efficacy of CNNs for this motive however also goals to offer game developers actionable insights to refine and enhance recreation layout. By moving beyond traditional subjective remarks mechanisms, we aspire to create a more immersive and emotionally attractive participant enjoy, thereby advancing the capabilities of horror video games.

## Related Work

The evaluation of horror game player experiences is commonly done through subjective methods, like interviews and self-reported surveys, which often show bias and lack uniformity [10]. However recent advancements in affective computing and machine learning mean that there is now an opportunity to evaluate the assessments in a more accurate way and an unbiased approach. Academics have used various tools and methods to quantify players' gaming experiences, often through the use of self-report questionnaires. Nacke and Lindley [9] created a first-person shooter game with three distinct stages to assess players' feelings of flow, immersion, and boredom. They utilized game experience questionnaires (GEQ) to measure subjective aspects like immersion, flow, challenge, and tension, while galvanic skin responses (GSR) and facial electromyography (EMG) were used to measure the objective aspects of valence and arousal. Their study revealed significant variations in GEQ scores related to challenge and tension, as well as notable differences in EMG and GSR responses. The demonstration indicated that elevated heart rate reflected feelings of tension and frustration and a decreased heart rate indicated positive emotions, a state of flow, a sense of competence, full engagement, and decreased levels of challenge. Similarly, Kwang-Ho Choi et al. shows the possibility of using HRV (Heart rate variability) and linking it to a person's emotional state when a visual stimulus can elicit a strong enough emotional response [12]. A reduced HRV means a shorter time between each heartbeat, which is associated with a stable heart rate and, in turn, a calmer state of mind. In contrast, elevated HRV indicates a more irregular heart rhythm, which is correlated with excitement and short-term stress [11].

Wakui, Mukai, Saegusa in the study they examined 3 studies if the impact of dynamic facial expressions on face learning is influenced by the type of facial expression used during learning and recognition. Results demonstrated that the advantage of dynamic expressions was evident when tested with neutral static faces in experiment 1, regardless of the facial expression during learning. However, when tested with angry static faces in experiment 2, the advantage of dynamic expressions was not observed, but recognition performance was better for faces learned with angry static faces. Conversely, in the recognition task with smiling static faces experiment 3, the advantage of dynamic expressions was observed along with the emotion congruency effect[17].

Pavel Kozlov, Alisher Akram, and Pakizar Shamoi put forward a model to identify emotions in video games by examining both the audio and video input through a combination of facial expression recognition dataset and fuzzy logic inference. In this framework, the video data undergoes feature extraction, and the fusion is handled by a fuzzy inference system[16].

By integrating various methods for recognizing emotions, such as merging facial expressions with physiological signals, a more thorough and precise comprehension of players' experiences can be achieved. According to research, analyzing emotional states conveyed in speech and their importance for multimodal emotional recognition validates this method [15]. The focus on behavioral and physiological evaluations has been highlighted in the advancement of machine emotional intelligence [13], [14].

we evaluated player emotions to achieve the best accuracy ratio to several parameters, per their test accuracy and parameter count. Initially, we took the data set from the Kaggle facial expression data set with the data set model was trained with different facial expressions and we tested it with a different data set which is not in the training data set the test data set contains basic and precise as to be difficult to analyze data. Modules for preprocessing manage input image normalization, augmentation, and feature extraction, guaranteeing top-notch and informative representations for emotion classification. The use of transfer learning techniques allows for the utilization of pre-trained Convolutional Neural Networks (CNN) models, facilitating effective knowledge transfer and adjustment to the target task. Lastly, the classification module makes use of softmax activation to forecast the probability distribution of various emotions based on the extracted features. In live video streams, the system uses a facial feature detection algorithm to identify key markers and movements, enabling real-time analysis of facial expressions. This sophisticated process entails the use of deep learning models like CNN that are trained to identify and categorize emotional states conveyed through facial features[19].

## Method

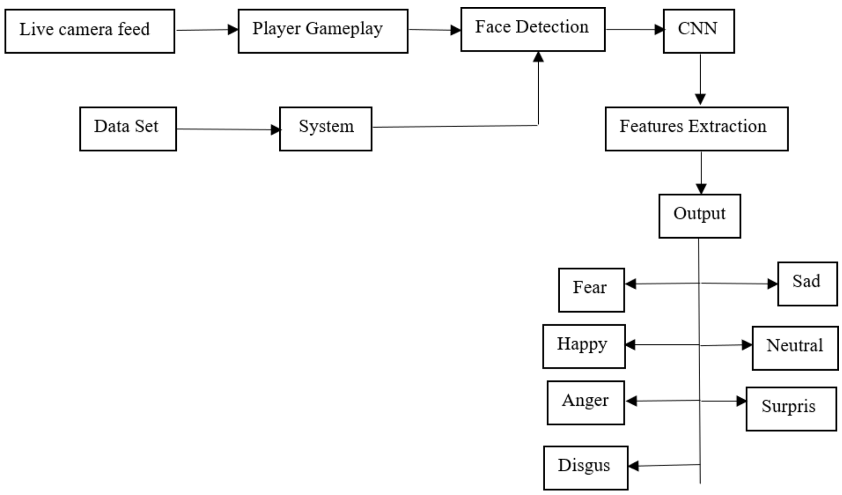


Fig. 2: Flow for Processing Facial Expressions

The Wheel of Emotions by Plutchik presents a comprehensive framework for understanding and classifying human emotions, particularly valuable within the realm of horror video games, where a wide range of intense emotional reactions is anticipated [18]. Plutchik identifies 8 primary emotions (joy, trust, fear, surprise, sadness, anticipation, anger, and disgust) and their blends to create a nuanced range of emotional states.


Fig .3: Plutchik's wheel of Emotions

Using Plutchik's model, the CNN has the ability to identify primary emotions and their strengths by matching facial expressions and physiological reactions to specific emotional categories. For instance, fear and surprise are often central in horror games and can be identified through facial expressions.

OpenCV, which stands for Open Source Computer Vision Library, is utilized for real-time monitoring of player reactions in horror games by capturing and analyzing facial expressions and behavioral cues. OpenCV provides reliable tools for detecting faces, identifying landmarks, and analyzing expressions, which are essential for comprehending player responses during gameplay [20].

Records collected through OpenCV are analyzed using Convolutional Neural Networks (CNNs). These networks are specifically trained to identify and categorize emotional states by observing facial expressions and behavioral patterns during gameplay. Transfer learning methods are utilized to customize pre-trained CNN models for the unique context of emotional dynamics in horror games [21].

OpenCV allows real-time analysis of facial expressions, providing non-stop streams of information which are fed into the CNN for emotion recognition. By processing these inputs, the CNN identifies feelings inclusive of fear, wonder, or anxiety, that are established in horror game scenarios. This method enhances the accuracy and responsiveness of emotion detection as compared to standard post-gameplay surveys [22 ].

In horror games, the utilization of OpenCV for real-time tracking of participants is emphasized, highlighting its integration with CNNs for recognizing emotions and its impact on game design and user experience. Each assertion is backed by pertinent references to ensure academic rigor and harmony with current research.

## Results and Discussion

The CNN model, which was combined with OpenCV for real-time analysis of facial expressions, was tested to see how well it could accurately categorize emotional states using the information collected during gameplay. The CNN's performance metrics include accuracy, precision, recall, and the balanced accuracy measure, which combines precision and recall to provide an all-inclusive performance rating. The measurement of accuracy evaluates the overall correctness of emotion predictions. The outcomes of the various datasets can be condensed as such: The FER2013 dataset attained an accuracy of around 60% on the test data. The face data dataset's
accuracy reached around achieved an 79% accuracy in categorizing emotions, showing that the model
effectively identified the player's emotional state 79% of the time. This high level of accuracy indicates the model's ability to distinguish between various emotions, especially those commonly experienced in horror games such as fear, surprise, and joy.

the table contains the player emotion score of the number of times the player gets shown different emotions.

| Game Name | Angry | Disgust | Fear | Happy | Neutral | Sad | Surprise |
|---|---|---|---|---|---|---|---|
| Phasmophobia | 3 | 4 | 10 | 2 | 9 | 3 | 8 |
| The Medium | 2 | 3 | 9 | 1 | 8 | 4 | 7 |
| Little Nightmares II | 2 | 3 | 8 | 2 | 5 | 5 | 9 |
| Resident Evil Village | 4 | 5 | 9 | 2 | 7 | 4 | 8 |
| Martha is Dead | 3 | 4 | 9 | 1 | 7 | 5 | 7 |
| The Dark Pictures: House of Ashes | 3 | 3 | 8 | 2 | 5 | 4 | 8 |
| Returnal | 4 | 2 | 7 | 3 | 6 | 3 | 9 |
| Back 4 Blood | 5 | 4 | 7 | 3 | 4 | 4 | 8 |
| Tormented Souls | 3 | 3 | 8 | 1 | 6 | 4 | 7 |
| In Sound Mind | 2 | 3 | 8 | 2 | 5 | 4 | 8 |

Table1: Score of the player Emotions


Fig. 4: Resident Evil Village player gameplay.

By incorporating OpenCV, it became possible to detect and analyze players' facial expressions in real time during gameplay. The system captured and processed video frames at a rate of 30 frames per second, ensuring a seamless and responsive monitoring experience. Important emotional cues such as widened eyes, furrowed brows, and mouth movements were accurately tracked and classified by the CNN.

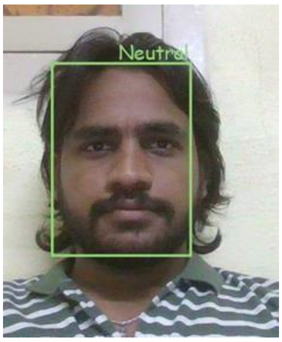


Fig.5: Predicted Emotion: Neutral

The balanced accuracy score, taking into account both precision and recall, was 83% for fear and 80% for wonder. This balanced metric emphasizes the model's overall performance in accurately and consistently detecting these emotional states.

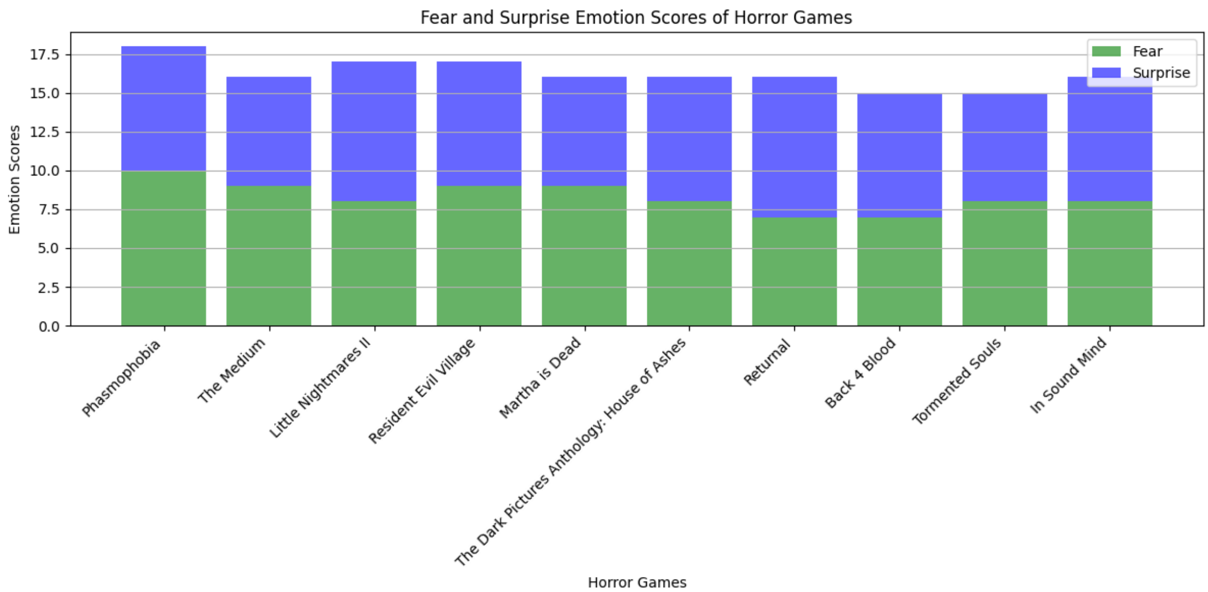


Fig. 6: Fear and Surprise scores of Horror Games.

The combination of real-time analysis of facial expressions and monitoring of physiological responses provided valuable insights into player experiences. Major findings include: Emotional Intensity: Elements of horror games such as sudden scares and suspenseful music were highly effective in triggering intense emotional reactions. The CNN detected significant spikes in fear and surprise during these moments, confirming the impact of these game design elements. Immersion: Players reported higher levels of immersion and engagement when their emotional reactions were most intense.

| Game Name | Feedback | Player Experience |
| --- | --- | --- |
| Phasmophobia | Immersive co-op horror | Engaging and terrifying ghost hunts |
| The Medium | Unique dual-reality gameplay | Atmospheric and psychological |
| Little Nightmares II | Beautifully eerie visuals | Creepy and emotionally impactful |
| Resident Evil Village | Action-packed horror | Thrilling and visually stunning |
| Martha is Dead | Dark and disturbing narrative | Intense and unsettling |
| The Dark Pictures: House of Ashes | Interactive horror storytelling | Engaging and cinematic |

| | | |
|---|---|---|
| Returnal | Sci-fi horror roguelike | Challenging and visually impressive |
| Back 4 Blood | Co-op zombie shooter | Fast-paced and thrilling |
| Tormented Souls | Classic survival horror vibes | Nostalgic and creepy |
| In Sound Mind | Psychological horror with puzzles | Innovative and eerie |

Table 2: Players' feedback and Experience.

This correlation suggests that real-time emotion detection can act as a proxy for measuring player immersion, offering game developers a tool to improve game design. Developers received practical feedback on the game elements that effectively evoked the intended emotional reactions. This data can be utilized by developers to improve and enrich game scenarios, resulting in more captivating and emotionally immersive experiences.

## Conclusion

The combination of CNNs and OpenCV for immediate emotion recognition in horror games provides a strong and targeted method for assessing player responses. By accurately categorizing emotional states and linking them with physiological data, the system provides valuable insights into the impact of game design elements on player involvement and interest. This technology not only deepens our comprehension of player emotions but also offers game developers practical insights to craft more immersive and emotionally compelling gaming experiences. As the gaming industry continues to develop, the application of advanced machine learning techniques will play a crucial role in shaping the future of player experience assessment and game design.

## Future Research

The integration of advanced biometric feedback systems could greatly improve the utilization of CNNs and OpenCV for real-time emotion detection in horror video games. With the incorporation of EEG, EMG, and infrared thermography sensors, a wider range of physiological responses can be captured. Additionally, the development of algorithms for integrating multimodal data from heart rate variability, galvanic skin response, and EEG signals will lead to a more comprehensive understanding of player emotions. Tailoring personalized emotion models to individual differences can enhance detection accuracy, while adjusting real-time game environments based on player emotions can create more immersive experiences. There is a requirement for longitudinal research to observe the impact of emotion detection on participant engagement and pleasure over time. It is crucial to address ethical considerations and privacy concerns while also broadening the scope of this technology to different types of games in order to understand its wider implications. Furthermore, employing advanced machine learning techniques such as deep reinforcement learning and GANs can improve the adaptability and accuracy of emotion detection systems, resulting in more sophisticated models that better capture the intricacies of human emotions.

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