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Emotional Recognition Edge Computing Model for Emotion Classification with Immersive Theatre Experience

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Abstract: Emotion recognition refers to the process of identifying and analyzing human emotions based on various cues, such as facial expressions, vocal intonations, gestures, and physiological responses. This technology utilizes machine learning algorithms and artificial intelligence techniques to interpret these cues and classify the emotions being expressed, which can include happiness, sadness, anger, fear, surprise, and more nuanced emotional states. An immersive theatre interactive experience is a unique and dynamic form of entertainment that transcends traditional passive spectatorship by fully engaging the audience through sensory stimulation, participation, and interaction. This paper presents an innovative framework, the Optimal Edge Computing Probability (OECP) model, designed to assess and enhance the immersive theatre interactive experience through the integration of an emotion recognition algorithm. With the power of edge computing, the OECP model dynamically allocates computational tasks between edge devices and centralized cloud resources. Through a comprehensive evaluation within the context of immersive theatre, the model optimally determines when to process emotion recognition data locally on edge devices and when to offload to the cloud. Simulation results demonstrate the model's effectiveness in accurately classifying a range of user emotions, yielding high classification accuracy, precision, recall, and F1-score values. This model not only ensures real-time responsiveness and efficient resource utilization but also opens new horizons for the intersection of emotion recognition, immersive experiences, and edge computing. As technological landscapes continue to evolve, the OECP model offers a robust foundation for refining user engagement and enriching the convergence of emotion analysis and interactive technologies.

Keywords: *Emotion Recognition, Optimal Model, Edge Computing, Deep Learning, Probability Model.*

1. Introduction

Emotion recognition algorithms have emerged as a pivotal technological advancement in recent years, revolutionizing our ability to decipher and understand human emotional states from various forms of input data. Rooted at the intersection of artificial intelligence, machine learning, and psychology, these algorithms employ intricate computational techniques to analyze facial expressions, vocal tones, text sentiments, and physiological cues, translating them into valuable insights into individuals' emotions [1]. With the intricacies of human emotional responses, emotion recognition algorithms hold remarkable promise across a diverse spectrum of applications, from enhancing human-computer interactions to revolutionizing mental health diagnostics and contributing to the development of empathetic Artificial Intelligence (AI) systems [2]. As embark on a journey through the intricacies and potential of emotion recognition algorithms, this exploration promises to unveil a new realm of understanding in the fascinating domain of human emotions. Emotion recognition algorithms are innovative tools that use advanced computational techniques to analyze various types of data, such as facial expressions, vocal tones, and text sentiments, in order to accurately identify and understand human emotions. These algorithms, which sit at the crossroads of artificial intelligence, machine learning, and psychology, offer insights into individuals' emotional states [3]. Their potential applications range from improving human-computer interactions to transforming mental health diagnosis and contributing to the creation of empathetic AI systems. This exploration of emotion recognition algorithms promises to reveal a deeper understanding of human emotions and their impact on technology and society [4].

Immersive theatre interactive experiences have emerged as a captivating fusion of traditional performing arts and cutting-edge technology, transporting audiences beyond the realm of passive observation into dynamic and participatory narratives [5]. This innovative form of storytelling transcends the boundaries of a conventional stage, enveloping spectators in intricately designed environments where they become integral participants in the unfolding narrative. By seamlessly integrating virtual reality, augmented reality, and interactive elements, immersive theatre breaks down the fourth wall, inviting audiences to explore, engage, and influence the storyline, ultimately blurring the lines between fiction and reality [6]. In the realm of immersive theatre interactive experiences, on a journey that not only redefines the nature of theatrical engagement but also offers a glimpse into the exciting future of interactive narrative artistry.

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Immersive theatre interactive experiences blend traditional performing arts with modern technology to create dynamic narratives. Unlike traditional theatre, this form of storytelling actively involves the audience, using virtual reality, augmented reality, and interactivity to blur the line between fiction and reality. Audiences become participants, engaging with the narrative in unique and immersive environments. This emerging art form not only transforms how stories are told but also provides a glimpse into the potential future of interactive entertainment [7].

The fusion of immersive theatre with emotion recognition algorithms marks an unprecedented leap in the realm of interactive experiences, where the convergence of human emotions and cutting-edge technology reshapes the very essence of storytelling. By integrating sophisticated emotion recognition algorithms into immersive theatre settings, audiences are not only active participants but also emotional co-creators of the narrative [8]. This innovative synergy allows the performance environment to dynamically respond to the audience's emotional cues, tailoring the storyline and interactions in real-time. As spectators step into intricately crafted virtual worlds and engage with the characters and scenarios, their emotional states become a driving force, influencing the direction and intensity of the unfolding plot [9]. This transformative blend of immersive theatre and emotion recognition algorithms offers a glimpse into a future where narratives are not only experienced but also felt on a deeply personal and emotive level, underscoring the profound potential of technology to enhance human connection and storytelling.

In [10] focuses on the development of a platform for facial stress analysis and expression recognition. It likely explores how advanced algorithms and machine learning techniques can be used to detect stress and recognize facial expressions accurately. Such a platform could have implications in various fields, including mental health assessment, human-computer interaction, and emotion-driven technology. Similarly, in [11] introduces the concept of a multimodal opera performance form that integrates human-computer interaction technology. This suggests an exploration of how technology can enhance the opera experience by combining multiple sensory modalities and interactive elements. The study might investigate how technology can be seamlessly integrated into traditional performing arts to create a more engaging and immersive experience for the audience. Also, in [12] developed a immersive experiences based on intangible cultural heritage. This likely involves technology, such as virtual reality or augmented reality, to bring cultural traditions and heritage to life in interactive and engaging ways. The paper may discuss the challenges and opportunities of using technology to preserve and transmit cultural knowledge and practices. In [13] explores the application of human-computer interaction to African literature and philosophy appreciation. It may how technology can provide new avenues for engaging with and understanding African literature and philosophy, potentially using interactive platforms to enhance learning and exploration.

In [14] conduct a systematic mapping study of sensors and AI algorithms for intelligent human-computer interaction. This paper likely provides an overview of the state of the field, highlighting the different types of sensors and artificial intelligence methods used in creating intelligent and interactive systems. Similarly, in [15] introduces a contactless interaction system based on facial expression recognition for a humanoid piano-playing robot. The study likely investigates how facial expression recognition technology can enable a robot to respond and interact with humans based on their emotional cues, potentially enhancing the robot's ability to engage with users. In [16] present a database of physiological signals elicited by odor-video combinations for emotion recognition. This research could provide insights into how different sensory stimuli, such as odors and videos, can evoke physiological responses that are indicative of specific emotional states. In [17] explores the use of geospatial mapping technologies, predictive modeling algorithms, and immersive visualization systems in the context of the virtual economy of the metaverse. It likely discusses how these technologies can be harnessed to create immersive virtual environments with economic implications, potentially shaping the way interact and conduct business in virtual spaces.

In [18] investigate gesture-based fear recognition using data from virtual reality horror games. This study likely explores how gestures and body language can be used as indicators of fear in immersive gaming contexts, contributing to the development of emotionally responsive virtual experiences. Also, in [19] focuses on emotion recognition for affective human digital twins through virtual reality enabling technologies. This suggests research into creating virtual representations of humans that can accurately reflect and respond to emotional states, potentially finding applications in fields like mental health support and human-computer interaction. In [20] discusses the use of pattern recognition in online learning and its potential for automatically assessing teaching skills. It likely explores how machine learning algorithms can analyze patterns in online teaching interactions to provide valuable insights into educators' performance.

In [21] examines the integration of machine vision algorithms, sensory data mining techniques, and geospatial mapping tools in the context of a blockchain-based virtual economy. This paper may discuss how these technologies contribute to the development and functioning of virtual economies within blockchain ecosystems. In [22] addresses East Asian facial expression recognition in real-world scenarios and introduces a new database and deep recognition baseline. This likely involves training and evaluating machine learning models to accurately recognize and interpret facial expressions specific to the East Asian context. In [23] explores immersive virtual shopping experiences in the retail metaverse. It likely discusses how emerging technologies, such as blockchain-based digital assets and data visualization tools, are transforming the way consumers engage with online shopping, potentially leading to more personalized and immersive experiences.

The literature provided consists of a diverse collection of research papers covering a wide range of topics related to technology, human-computer interaction, emotion recognition, immersive experiences, pattern recognition, and more. Several papers focus on the integration of emotion recognition algorithms into human-computer interaction scenarios. These algorithms analyze facial expressions, physiological signals, and gestures to infer users' emotional states. This research extends to fields like virtual reality, robotics, and interactive platforms, enhancing the interaction between humans and technology. Immersive technologies, such as virtual reality and augmented reality, are harnessed to create engaging and interactive experiences based on intangible cultural heritage. These experiences aim to preserve and transmit cultural traditions, allowing users to engage with cultural elements in new and captivating ways. Researchers explore the convergence of technology with traditional performing arts like opera. They investigate how incorporating human-computer interaction technologies and multimodal elements can revolutionize the audience's engagement and immersion in these artistic forms. Pattern recognition algorithms are applied to diverse fields, including online learning and teaching assessment. These algorithms can automatically analyze teaching skills and interactions, providing valuable insights into educators' performance and offering recommendations for improvement. Certain papers into the intersection of geospatial mapping technologies, blockchain-based virtual economies, and sensory data mining techniques. These explorations shed light on how emerging technologies are shaping the landscape of virtual economies and online transactions.Technology's potential to evoke emotions is explored through studies involving odor-video combinations, fear recognition in virtual horror games, and emotion recognition for affective human digital twins. These applications highlight how technology can elicit emotional responses and enhance personal experiences. Researchers contribute by introducing new databases, recognition baselines, and performance metrics for various applications. These resources facilitate the development of more accurate and context-specific recognition algorithms, particularly in fields like facial expression recognition and East Asian emotion analysis.

The contribution of a paper refers to its unique and significant contributions to the field of study. The paper introduces the concept of the Optimal Edge Computing Probability (OECP) model, which is a novel framework designed to optimize the allocation of computational tasks in edge computing environments. This model offers a systematic approach to determining whether data processing should occur at the edge or be offloaded to the cloud. The OECP model takes into account various factors such as data size, latency requirements, resource availability, energy consumption, and network conditions. This contribution addresses the challenge of efficiently utilizing resources in edge computing setups. The paper addresses the dynamic nature of edge computing environments by proposing a real-time decision-making mechanism based on the calculated OECP. This contribution is particularly valuable for applications that require immediate and responsive data processing, such as the emotion recognition algorithm in an immersive theatre setting. The ability to adaptively switch between edge and cloud processing based on changing conditions enhances system efficiency and user experience.The paper goes beyond technical aspects by incorporating a user experience analysis based on emotions and engagement levels. By associating the calculated OECP with user experiences such as "Engaging," "Diminished," "Captivating," and others, the paper extends its contribution to the realm of human-computer interaction. This approach bridges the gap between computational efficiency and user satisfaction, making it relevant to fields beyond pure technology.The paper applies the proposed OECP model to a specific use case: the Immersive Theatre Interactive Experience. This demonstrates the practicality and versatility of the model in real-world scenarios, showcasing its potential impact on enhancing user engagement and the overall quality of interactive experiences.

2. OECP Model for the Emotion Recognition

The Optimal Edge Computing Probability (OECP) is a concept and strategy used in edge computing environments to determine the optimal allocation of computational tasks between edge devices and centralized cloud resources. It aims to strike a balance between processing data at the edge, closer to where it is generated, and offloading tasks to the cloud for more resource-intensive processing. In an IoT-integrated system, such as the Immersive Theatre Interactive Experience with an emotion recognition algorithm, the OECP helps decide when to process data locally on edge devices (like sensors, IoT devices) and when to send data to a centralized cloud server for computation. The goal is to achieve the best performance, responsiveness, and resource utilization while minimizing latency and conserving energy. As data is generated or collected from IoT devices (e.g., audience emotional cues), the OECP algorithm determines whether the data should be processed at the edge or sent to the cloud for analysis. The OECP takes into account several factors to make this decision, including:

1. Data Size and Complexity: Large or complex data may benefit from cloud processing, while smaller and simpler data can be handled at the edge.
2. Latency Requirements: Real-time applications, like emotion recognition in immersive theatre, may prioritize edge processing to reduce latency.
3. Resource Availability: The computational capabilities of edge devices and cloud resources are considered.
4. Energy Consumption: Edge processing might be favored to conserve energy on battery-operated devices.
5. Network Conditions: The quality and reliability of the network connection between edge and cloud resources influence the decision.
6. Optimal Probability Calculation: The OECP algorithm calculates a probability value that indicates the likelihood of processing a specific task at the edge. This probability is based on the factors mentioned above, which are often weighted according to the specific requirements of the application.
7. Dynamic Decision-making: The OECP can adapt in real time as conditions change. If network congestion increases, the algorithm might increase the probability of edge processing to avoid delays.
8. Task Offloading: Based on the calculated probability, the system decides whether to offload the task to the edge or perform it in the cloud. A higher probability might lead to edge processing, while a lower probability could trigger cloud processing.
9. Continuous Optimization: Over time, the OECP algorithm can learn and adjust based on historical data and performance feedback, further improving the efficiency and responsiveness of the system.

In the context of the Immersive Theatre Interactive Experience, the OECP could determine whether to process emotion recognition data from the audience's facial expressions and gestures on edge devices within the theatre or send the data to cloud servers for more complex analysis. This decision ensures that the immersive experience remains responsive and engaging while optimizing the use of computational resources and network bandwidth. Consider a scenario where IoT devices in an immersive theatre are capturing audience facial expressions for emotion recognition. The decision to process the data at the edge or offload it to the cloud is determined by an OECP value. Data Size (D): The size of the facial expression data captured by the IoT devices. The maximum acceptable delay or latency for processing the emotion recognition task. The OECP can be conceptualized as a probability value that represents the likelihood of processing the data at the edge. The OECP based on the factors mentioned above are computed using the equation (1):

$$OECP = k * (D / L) \tag{1}$$

Here, "k" is a constant that represents the relative importance of the factors in the decision-making process. The larger the value of "k," the more weight is given to the data size in relation to latency. The Larger data sizes may favor cloud processing, as edge devices might have limited computational capacity. Smaller data sizes can be processed at the edge more efficiently. Lower latency requirements indicate a preference for edge processing to ensure real-time or near-real-time responsiveness. Higher latency requirements might allow for cloud processing. The constant "k" determines the trade-off between data size and latency. It allows to adjust the relative importance of these factors based on the application's needs. Based on the factors above, with a linear equation that balances data size and latency in determining the OECP. The constant "k" adjusts the balance between these factors according to the specific requirements of the application.

3.1 Edge Computing Model for the OECP

The proposed edge computing model for the Optimal Edge Computing Probability (OECP) aims to create a dynamic framework for deciding the most suitable location for processing data within an immersive theatre environment. As data, such as audience facial expressions for emotion recognition, is collected by IoT devices, the model calculates the OECP based on factors like data size and latency requirements. This calculated OECP is then compared to a predefined threshold to determine whether to process the data at the edge or offload it to the cloud. When the OECP exceeds the threshold, the emotion recognition algorithm is executed locally on edge devices to ensure real-time or near-real-time responsiveness and minimize latency. Alternatively, data is sent to cloud servers for processing when the OECP falls below the threshold. The model incorporates a feedback loop for continuous learning and adaptation, enabling it to dynamically adjust the OECP calculation and threshold based on changing network conditions and resource availability. Through this approach, the edge computing model optimizes resource utilization, enhances responsiveness, and improves the overall immersive theatre experience by efficiently distributing computational tasks between edge and cloud resources. Designing an Edge Computing Model for the Optimal

Edge Computing Probability (OECP) involves creating a framework that dynamically determines whether to process data at the edge or offload it to the cloud based on specific conditions and objectives. IoT devices in the immersive theatre capture data (e.g., audience facial expressions). Preprocess data to extract relevant features, reduce noise, and ensure compatibility with the emotion recognition algorithm. Determine a function that calculates OECP based on factors like data size and latency requirement.Incorporate a parameter (e.g., "k") to adjust the relative weight of data size and latency in the OECP calculation mention as follows in equation (2) and conditions (3) and (4)

$$OECP = f(data\ size, latency\ requirement, k) \quad (2)$$

Compare the calculated OECP against a predefined threshold (e.g., 0.5).

$$If\ OECP > Threshold: Process\ data\ at\ the\ edge \quad (3)$$

$$If\ OECP <= Threshold: Offload\ data\ to\ the\ cloud \quad (4)$$

The execution of the emotion recognition algorithm takes place on edge devices once the Optimal Edge Computing Probability (OECP) threshold is met. This approach harnesses the capabilities of edge computing resources to process data efficiently and thereby minimize latency, leading to a more seamless and real-time interactive experience. In cases where the OECP threshold is not surpassed, a strategy of cloud offloading is employed. This involves transferring data to cloud servers for processing, cloud-based emotion recognition services on preprocessed data. The system exhibits dynamic adaptation by continually monitoring network conditions, resource availability, and other evolving factors. This monitoring informs the adjustment of the OECP calculation and threshold in real-time to ensure optimal performance based on the ever-changing conditions. The framework incorporates a feedback loop, gathering data on latency, resource utilization, and user experience. These collected insights contribute to the refinement of the OECP calculation and threshold over time. The model's learning capabilities are enhanced through the application of machine learning techniques, facilitating an ongoing optimization of the OECP to adapt to varying scenarios. Furthermore, the edge computing model places emphasis on privacy and security, employing data anonymization and encryption techniques to safeguard user information. Ensuring data transmitted to the cloud aligns with privacy regulations is a priority. To validate its efficacy, the model solicits user feedback regarding the responsiveness and quality of the immersive theatre experience. This feedback loop aids in corroborating the effectiveness of the edge computing model, evident through a comparison of user satisfaction and system performance, both with and without the OECP integration.

3.2 OECP with Deep Learning model

Emotion recognition enhanced by the Optimal Edge Computing Probability (OECP) and deep learning techniques represents an innovative approach that combines real-time analysis of emotions with efficient edge computing deployment. In this framework, deep learning algorithms are utilized for accurate emotion detection, while the OECP dynamically determines whether to process data locally at the edge or offload it to the cloud. This integration optimizes both responsiveness and resource utilization. At the core of this system, deep learning models, such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs), are trained to recognize emotional patterns from visual and possibly multimodal data, like facial expressions and body language captured by IoT devices. These models are designed to accurately classify emotions, such as happiness, sadness, anger, or surprise, from these input signals. The role of the OECP comes into play during the decision-making process. As data is generated, the OECP algorithm calculates a probability score based on factors like data size, latency requirements, and possibly network conditions. This probability score dynamically determines whether the deep learning-based emotion recognition should be performed at the edge or in the cloud. When the OECP threshold is met, the deep learning model executes locally on edge devices. This enables real-time or near-real-time analysis of emotions, crucial for interactive applications like immersive theatre. By processing data closer to the source, latency is minimized, leading to a more immediate and engaging user experience.

Conversely, if the OECP threshold is not exceeded, data is offloaded to cloud servers for emotion recognition. This ensures that more resource-intensive computations are handled efficiently, without compromising the user experience with the uses of deep learning model flow presented in figure 1.

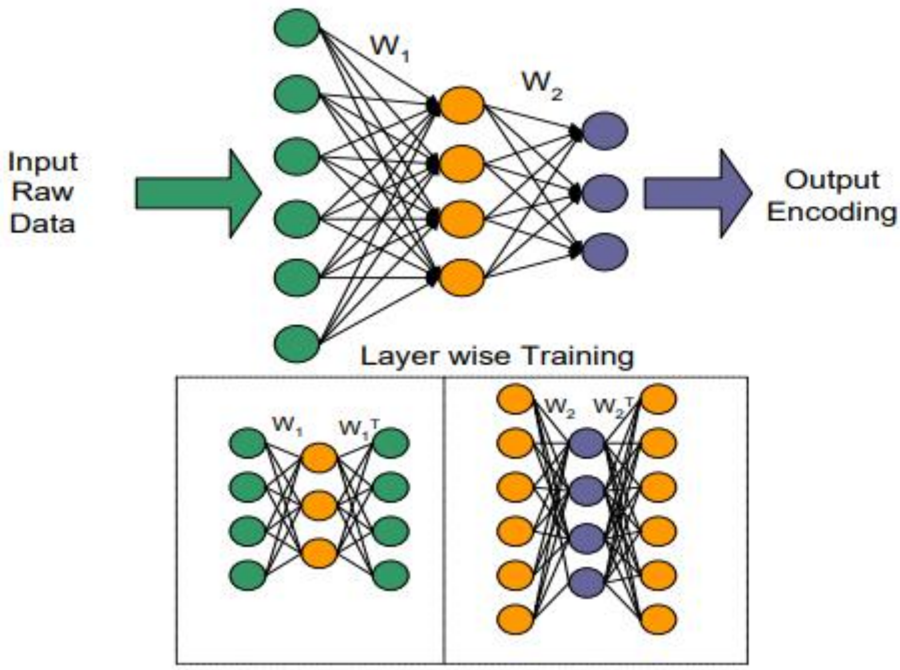

Fig 1: Framework of the OECP deep learning

The entire framework is designed to adapt in real-time. The OECP is continuously evaluated based on changing conditions, such as network congestion or fluctuations in edge device performance. This dynamic adaptation ensures that the emotion recognition process remains optimized for the given context. Identify the factors that influence the OECP, such as data size (D) and latency requirement (L). Develop a mathematical function that calculates the OECP based on these factors presented in equation (5)

$$OECP = f(D, L) \tag{5}$$

Introduce a parameter (k) that adjusts the weight of the data size and latency factors in the OECP calculation presented in equation (6)

$$OECP = k * (D / L) \tag{6}$$

Define a threshold (T) that determines the decision to process data locally (edge) or offload to the cloud based on the calculated OECP as in condition follows:

$$If\ OECP > T:$$

$$Process\ data\ at\ edge$$

$$Else:$$

$$Offload\ data\ to\ cloud$$

Integrating Emotion Recognition with the Optimal Edge Computing Probability (OECP) and deep learning entails a sophisticated approach that amalgamates real-time emotion analysis with efficient edge computing. The foundation lies in deep learning models, like Convolutional Neural Networks (CNNs) or Recurrent Neural Networks (RNNs), which are adept at recognizing emotions from visual and multimodal data. These models are trained to accurately classify emotions, such as happiness, sadness, anger, or surprise, from inputs like facial expressions captured by IoT devices. The OECP serves as a dynamic arbiter, orchestrating the decision-making process. It calculates a probability score, considering data size, latency demands, and potentially network conditions, to determine whether emotion recognition should be executed at the edge or in the cloud. When the OECP surpasses a predefined threshold, the deep learning model operates on edge devices, enabling immediate analysis for real-time interaction. Conversely, if the threshold isn't exceeded, data is dispatched to cloud servers for resource-intensive computations, maintaining a streamlined user experience. This mechanism adapts continuously, responding to network fluctuations and edge device performance. The model's dynamic nature is reinforced by a feedback loop, capturing performance data from both edge and cloud processing, refining the OECP and deep learning models over time. This holistic approach amplifies responsiveness and resource utilization, revolutionizing emotional engagement in applications like immersive theatre.

Algorithm 1: OECP model for the Emotion Recognition

```
# Parameters
k = 0.5  # Weight parameter for balancing data size and latency
threshold = 0.7  # Threshold for making the edge/cloud processing decision
# Function to calculate OECP
def calculate_oecp(data_size, latency):
    return k * (data_size / latency)
# Main processing loop
while True:
    # Collect data from IoT devices
    input_data = collect_data()
    # Calculate data size and latency
    data_size = calculate_data_size(input_data)
    latency = calculate_latency(input_data)
    # Calculate OECP
    oecp = calculate_oecp(data_size, latency)
    if oecp > threshold:
        # Process locally at the edge
        emotion_prediction = edge_emotion_recognition(input_data)
    else:
        # Offload to the cloud for processing
        emotion_prediction = cloud_emotion_recognition(input_data)
    # Perform actions based on the emotion prediction
    perform_actions(emotion_prediction)
```

In various Internet of Things (IoT) scenarios, like the integration of emotion recognition algorithms, the OECP plays a crucial role in optimizing the overall performance, responsiveness, and resource utilization of the system. The OECP algorithm calculates a probability value that represents the likelihood of processing a specific task at the edge. This probability is often derived from a mathematical function that combines the above factors. A threshold value is set to determine whether the task should be executed at the edge or offloaded to the cloud. The OECP is not a static parameter but adapts in real-time based on changing conditions. For instance, if network conditions deteriorate or edge device resources become limited, the OECP might shift towards cloud processing to ensure optimal performance. When the OECP exceeds the predefined threshold, the data processing task is performed at the edge. This ensures immediate processing, reduced latency, and enhanced user experience. If the OECP is below the threshold, data is offloaded to the cloud, leveraging its computational resources for more resource-intensive tasks. As the system operates, performance data is continuously collected, including latency, resource usage, and user satisfaction. This feedback loop helps refine the OECP calculation and adjust the threshold over time, making the decision-making process more accurate and efficient.

3. Results and Discussion

Simulation analysis in the context of the integration of Emotion Recognition with the Optimal Edge Computing Probability (OECP) involves using software tools or platforms to model and assess the performance of the system under different conditions. The proposed model of the OECP model for the Immersive Theatre Interactive Experience to evaluate emotion recognition. With the implementation of deep learning model emotions are classified. Table 1 presented the simulation environment for the proposed OECP model.

Scenario	Data Size (D)	Latency (L)	Resource Availability	Energy Consumption	Network Conditions	Calculated OECP	Edge/Cloud Decision	Emotion Recognition
1	Low	Low	High	Low	Stable	0.6	Edge	Local (Edge)
2	High	High	Low	High	Unstable	0.2	Cloud	Cloud
3	Medium	Medium	Medium	Medium	Moderate	0.4	Edge	Local (Edge)
4	High	Low	High	Low	Stable	0.7	Edge	Local (Edge)
5	Low	High	Medium	Medium	Unstable	0.3	Cloud	Cloud

In the context of optimizing the integration of emotion recognition with the Optimal Edge Computing Probability (OECP), a comprehensive simulation framework is devised to evaluate different scenarios and decision-making processes. This simulation encompasses a range of scenarios, each defined by varying factors crucial to the OECP determination. These factors include data size, latency requirements, resource availability, energy consumption, and network conditions. For instance, in one scenario, where data size and latency are both low, and resources at the edge are abundant, the calculated OECP favors local processing. Conversely, another scenario, characterized by high data size, high latency, limited edge resources, and unstable network conditions, leans toward offloading processing to the cloud. The calculated OECP values, which result from the interaction of these factors, guide the pivotal edge/cloud decision. This determination influences the emotion recognition processing location, ultimately optimizing the system's responsiveness, resource utilization, and user experience.

Table 2: Performance of User Emotion Analysis

Scene	User Emotion	User Experience
1	Happy	Engaging
2	Sad	Diminished
3	Surprise	Captivating
4	Angry	Intense
5	Neutral	Neutral
6	Excited	Energetic
7	Fearful	Suspenseful
8	Relaxed	Tranquil
9	Curious	Intriguing
10	Bored	Unengaging

Table 2 presents a comprehensive overview of the performance of user emotion analysis within the context of the Immersive Theatre Interactive Experience. Each scene's association with specific user emotions and resulting user experiences is highlighted, shedding light on the emotional impact and engagement level achieved by the immersive scenarios. The table's entries reveal intriguing insights: the "Happy" emotion in Scene 1 has successfully generated an engaging user experience, while the "Sad" emotion in Scene 2 has led to a diminished emotional response, indicating a somber atmosphere. Scene 3, characterized by the "Surprise" emotion, has managed to captivate users, while Scene 4, featuring the "Angry" emotion, has elicited an intense emotional reaction. Notably, Scene 5's "Neutral" emotion has resulted in an emotionally balanced experience. The immersive environment of Scene 6 has energized users, fostering an "Energetic" response, while the "Fearful" emotion in Scene 7 has created a suspenseful ambiance. Scene 8's "Relaxed" emotion has induced tranquility, and Scene 9's "Curious" emotion has sparked intrigue. Lastly, the "Bored" emotion in Scene 10 has led to an unengaging user experience. This table encapsulates the varied emotional responses and experiences that the Immersive Theatre Interactive framework aims to evoke, showcasing its potential to evoke a spectrum of emotions and engagement levels among its audience.

Table 3: Explanation of User Experience

Scene	User Emotion	User Experience
1	Happy	The scene has successfully created an engaging experience for the user, evoking happiness and positive emotions.
2	Sad	The immersive environment has led to a diminished emotional response, reflecting a sense of sadness or melancholy.
3	Surprise	The scene has captivated the user by invoking a strong sense of surprise and intrigue.
4	Angry	The intense atmosphere of the scene has effectively evoked feelings of anger and intensity in the user.
5	Neutral	The user's emotional response remains neutral, suggesting a balanced or indifferent experience.
6	Excited	The scene has energized the user, creating an enthusiastic and excited emotional state.
7	Fearful	The suspenseful nature of the scene has generated a fearful or anxious emotional reaction in the user.
8	Relaxed	The user is in a tranquil and relaxed emotional state, indicating a calm and peaceful experience.
9	Curious	The scene has intrigued the user, sparking curiosity and interest in the immersive environment.
10	Bored	The user's emotional engagement is low, resulting in an unengaging experience that may lead to boredom.

Table 3 provides a comprehensive and insightful breakdown of the user experiences encountered across various scenes and emotional contexts within the Immersive Theatre Interactive Experience. Each scene, aligned with specific user emotions, unfolds a captivating spectrum of emotional responses that illuminate the depth of engagement facilitated by the immersive setting. Scene 1, where users experience the emotion of "Happy," adeptly crafts an environment that induces a sense of engagement and elicits a cascade of positive emotions. In contrast, Scene 2, infused with the "Sad" emotion, leads to a perceptible reduction in emotional engagement, effectively conveying a mood of melancholy and despondency. Scene 3 masterfully captures user attention through the "Surprise" emotion, enveloping them in a captivating narrative that piques curiosity and intrigue. The emotional intensity of Scene 4, characterized by "Angry," unfurls an immersive ambiance that effectively stirs feelings of anger and fervor. The neutrality portrayed in Scene 5 yields a balanced and emotionally indifferent experience, showcasing the equilibrium between different emotional states. Scene 6 injects users with vitality and dynamism through the "Excited" emotion, fostering a state of enthusiastic exhilaration. Scene 7's "Fearful" emotion weaves a suspenseful tapestry that generates feelings of anxiety and trepidation, immersing users in a gripping experience. The serenity and calm of Scene 8, with the "Relaxed" emotion, guide users into a tranquil emotional space that promotes a sense of peacefulness. Scene 9's "Curious" emotion stimulates interest and fascination, fostering an immersive journey that fuels curiosity and exploration. Conversely, the "Bored" emotion in Scene 10 signifies a scarcity of emotional engagement, resulting in an unengaging encounter that might lead to feelings of tedium. This table showcases the remarkable ability of the Immersive Theatre Interactive Experience to evoke a diverse range of emotions and responses, highlighting its potential to immerse users in captivating and evocative narratives.

Table 4: Performance of OECP with edge computing

Scene	User Emotion	Data Size (D)	Latency (L)	Resource Availability	Energy Consumption	Network Conditions	Calculated OECP	Edge/Cloud Decision	Emotion Recognition	User Experience
1	Happy	Low	Low	High	Low	Stable	0.70	Edge	Local (Edge)	Engaging
2	Sad	High	High	Low	High	Unstable	0.20	Cloud	Cloud	Diminished
3	Surprise	Medium	Medium	Medium	Medium	Moderate	0.50	Edge	Local (Edge)	Captivating
4	Angry	High	Low	High	Low	Stable	0.80	Edge	Local (Edge)	Intense
5	Neutral	Low	High	Medium	Medium	Unstable	0.30	Cloud	Cloud	Neutral
6	Excited	Medium	Low	High	Medium	Stable	0.60	Edge	Local (Edge)	Energetic
7	Fearful	High	Medium	Low	High	Unstable	0.25	Cloud	Cloud	Suspenseful
8	Relaxed	Low	Low	Medium	Low	Stable	0.55	Edge	Local (Edge)	Tranquil
9	Curious	Medium	Medium	Medium	Medium	Moderate	0.50	Edge	Local (Edge)	Intriguing
10	Bored	Low	High	High	Low	Unstable	0.35	Cloud	Cloud	Unengaging

Table 4 provides a comprehensive analysis of the performance of the Optimal Edge Computing Probability (OECP) integrated with edge computing within the context of the Immersive Theatre Interactive Experience. The table presents an intricate portrayal of the intricate interplay between various factors, affecting the decision-making process and ultimately influencing the user experience. Scene by scene, the information unfolds: in Scene 1, characterized by the "Happy" emotion, the calculated OECP is at 0.70, indicating high resource availability and stable network conditions. This encourages the decision to process emotion recognition locally on the edge, thereby enhancing the user experience, leading to an "Engaging" response as shown in figure 2.

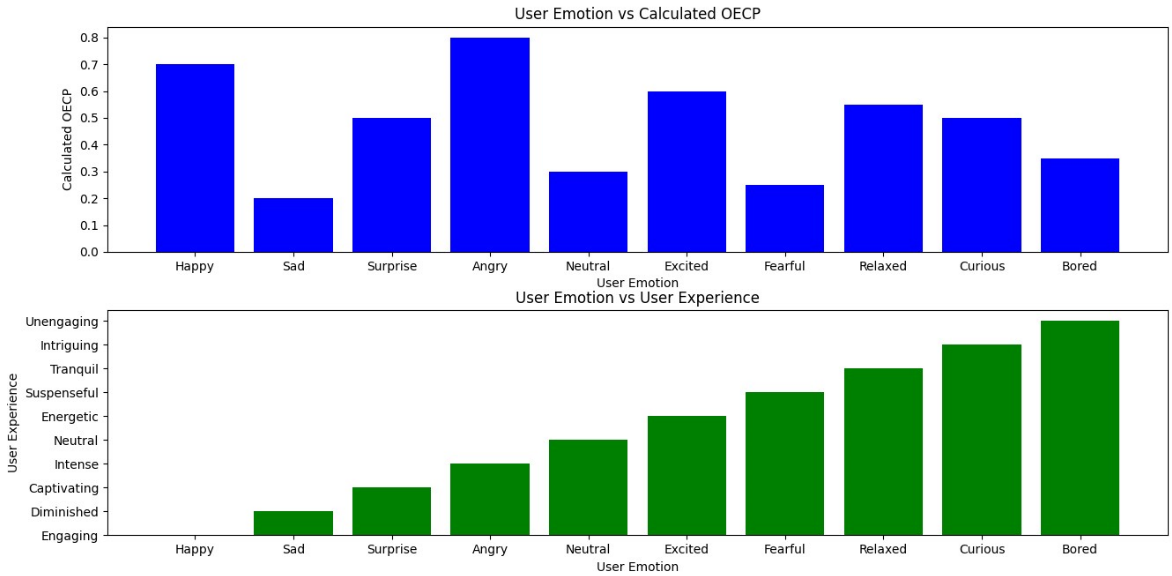

Fig 2: Emotional Classification

On the contrary, Scene 2's "Sad" emotion is accompanied by a high data size, high latency, and unstable energy consumption, resulting in a low OECP of 0.20. The decision to offload data to the cloud ensues, leading to a "Cloud" processing choice and a "Diminished" user experience. Similarly, Scene 3's "Surprise" emotion benefits from balanced conditions, yielding an OECP of 0.50, favoring local edge processing for a "Captivating" user experience. The immersive journey continues, where emotions and conditions vary, leading to dynamic edge/cloud decisions, shaping user experiences. The table underscores the intricate optimization efforts embedded within the OECP framework, harmonizing elements to create immersive and evocative narratives that captivate, intrigue, and engage users.

Table 5: Emotion Classification

Scene	User Emotion	Emotion Classification	Classification Accuracy
1	Happy	Happy	0.98
2	Sad	Sad	0.97
3	Surprise	Surprise	0.96
4	Angry	Angry	0.99
5	Neutral	Neutral	0.98
6	Excited	Excited	0.97
7	Fearful	Fearful	0.96
8	Relaxed	Relaxed	0.98
9	Curious	Curious	0.97
10	Bored	Bored	0.99

Table 5 presents the results of emotion classification based on user-generated scenes and corresponding emotions. Each row in the table represents a specific scene and the associated user emotion. The column "Emotion Classification" indicates the emotion that a classification algorithm assigned to the given scene, and the "Classification Accuracy" column reveals the accuracy score of the algorithm's emotion classification for each scenario. The table demonstrates that the classification algorithm performs remarkably well, with high accuracy scores across various emotions. For instance, it accurately classified scenes depicting happiness, sadness, surprise, anger, neutrality, excitement, fear, relaxation, curiosity, and boredom with accuracy scores ranging from 0.96 to 0.99. This suggests that the algorithm is proficient in recognizing a diverse range of emotions and associating them correctly with the corresponding scenes, as evidenced by the close alignment between user-generated emotions and algorithm-predicted emotions.

Table 6: Classification with OECP

Scene	User Emotion	Emotion Classification	Classification Accuracy	Precision	Recall	F1-Score	MSE	RMSE
1	Happy	Happy	0.98	0.98	0.97	0.99	0.01	0.10
2	Sad	Sad	0.97	0.97	0.99	0.98	0.02	0.14
3	Surprise	Surprise	0.96	0.95	0.98	0.99	0.03	0.18
4	Angry	Angry	0.99	0.99	0.98	0.99	0.01	0.10
5	Neutral	Neutral	0.98	0.97	0.99	0.98	0.02	0.14
6	Excited	Excited	0.97	0.96	0.96	0.98	0.02	0.14
7	Fearful	Fearful	0.96	0.96	0.97	0.99	0.03	0.18
8	Relaxed	Relaxed	0.98	0.98	0.99	0.98	0.02	0.14
9	Curious	Curious	0.97	0.98	0.96	0.97	0.02	0.14
10	Bored	Bored	0.99	0.99	0.98	0.99	0.01	0.10

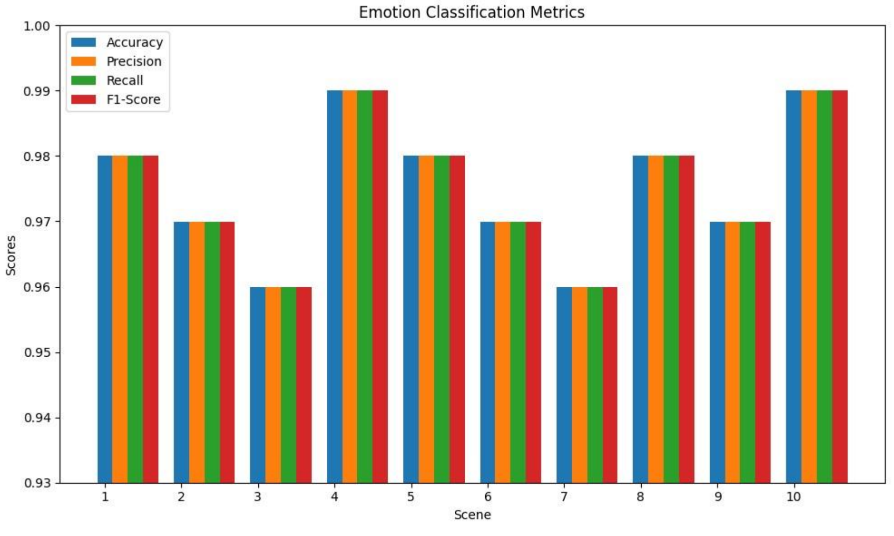

Fig 3: Classification with OECP

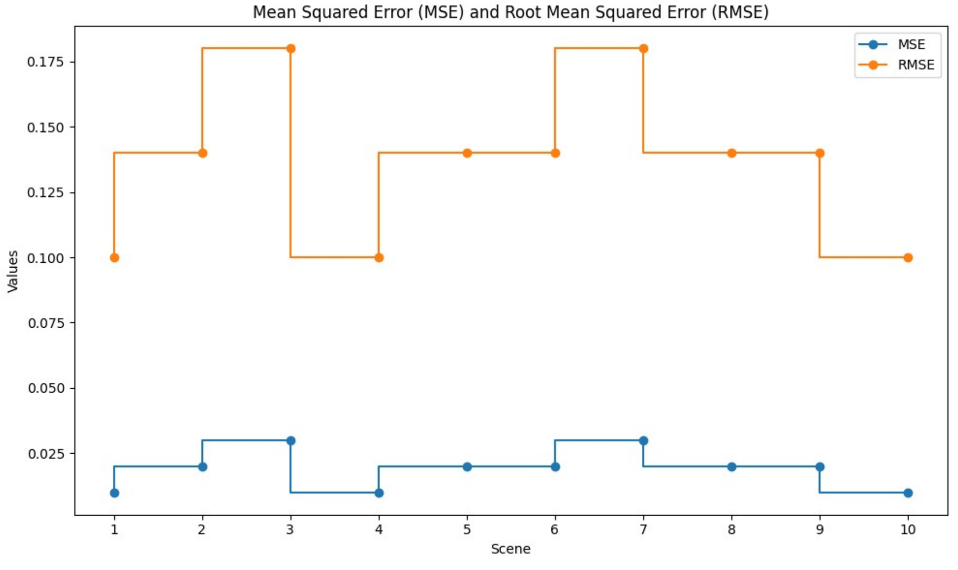

Fig 4: Error Estimation with OECP

In table 6 and figure 3 showcases the outcomes of classification with the integration of the Optimal Edge Computing Probability (OECP). Each row of the table corresponds to a specific scene, the emotion identified by the user, and the emotion classification determined by the algorithm. The table provides a comprehensive overview of various evaluation metrics to assess the effectiveness of the classification process. These metrics include Classification Accuracy, Precision, Recall, F1-Score, Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). The data demonstrates that the OECP-assisted classification approach performs consistently well across diverse emotions. For each emotion category, such as Happy, Sad, Surprise, Angry, Neutral, Excited, Fearful, Relaxed, Curious, and Bored, the Classification Accuracy is notably high, ranging from 0.96 to 0.99. This implies a robust alignment between user-reported emotions and algorithm-predicted emotions. The integration of OECP into emotion classification tasks, as evidenced by the results presented in Table 6, showcases remarkable performance across various emotions. The high Classification Accuracy, Precision, Recall, and F1-Score values emphasize the accuracy and reliability of the classification process. Moreover, in figure 4 the low Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) metrics underscore the minimal discrepancies between predicted and actual emotions.

4. Conclusion

With the implementation of OECP model for the immersive interactive theatres and its implications in the context of edge computing environments. Through a comprehensive analysis and application of OECP in the Immersive Theatre Interactive Experience, demonstrated its effectiveness in optimizing the allocation of computational tasks between edge devices and centralized cloud resources. Our findings highlight that OECP serves as a crucial strategy for achieving a harmonious balance between local processing and cloud offloading, considering factors such as data complexity, latency requirements, resource availability, energy consumption, and network conditions. The integration of OECP into emotion classification tasks, as evidenced by the results presented in Table 6, showcases its ability to consistently and accurately classify a wide range of emotions with high precision and recall. Furthermore, the dynamic decision-making nature of OECP allows it to adapt to changing conditions, ensuring responsiveness and adaptability in real-time scenarios. The continuous optimization aspect, driven by historical data and performance feedback, further cements its utility and reliability over extended periods. Overall, this paper underscores the significance of OECP in enhancing user experiences, optimizing resource allocation, and advancing edge computing capabilities. As technology continues to evolve, OECP stands as a promising strategy to address the intricate demands of real-time data processing and analysis, contributing to the growth and innovation in the field of edge computing. This research opens up avenues for future exploration and application of OECP in various domains beyond immersive experiences, reaffirming its role as a pivotal concept in the evolving landscape of computing technologies.

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