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# Virtual Reality User Experience classifier employing Deep Learning for Design Enhancement

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**Abstract**

This thesis focuses on the design and implementation of a Virtual Reality (VR) User Experience Classification system using deep learning to improve the quality and effectiveness of VR application design. The proposed system is developed using a large-scale VR user experience dataset containing more than 10,000 interaction records collected from diverse virtual environments. A key challenge addressed in this study is class imbalance, where approximately 60% of the data belongs to a majority class while the remaining 40% represents minority classes. Conventional classification techniques often fail to handle such imbalance effectively, resulting in limited predictive performance and evaluation metrics typically below 75%. Moreover, traditional and manual VR user experience assessment methods struggle with poor generalization across varied user behaviors and limited capability to capture complex interaction patterns. To address these challenges, this research introduces a hybrid framework that integrates the Synthetic Minority Over-sampling Technique (SMOTE) with a Deep Neural Network (DNN) classifier. SMOTE balances the dataset by generating synthetic samples for minority classes, while the DNN automatically learns hierarchical features and complex relationships within VR interaction data. The proposed model is evaluated using a train–test split approach and compared against baseline classifiers. Experimental results show that the SMOTE–DNN model achieves over 99% accuracy, precision, recall, and F1-score, demonstrating its robustness and effectiveness for VR user experience classification and design optimization.

**Keywords:** Virtual Reality, User Experience Classification, Deep Neural Network, SMOTE, Class Imbalance, Machine Learning, VR Design Evaluation

## 1. Introduction

Virtual Reality (VR) has emerged as a transformative technology across various industries including gaming, healthcare, education, and retail. According to a report by Statista, the global virtual reality market size stood at approximately $15.81 billion in 2020 and is projected to reach $87 billion by 2030, reflecting the massive adoption potential of immersive technologies. VR has been instrumental in creating simulated environments that mimic real-world experiences, enabling users to interact with computer-generated 3D environments in a more intuitive and engaging way. As VR applications expand across industries, understanding and improving user experience has become a crucial aspect of its development and deployment.

The usability and effectiveness of VR systems are closely tied to user satisfaction, cognitive engagement, and physical comfort. Studies show that over 38% of users discontinue VR usage due to factors such as disorientation, eye strain, and complex navigation. This emphasizes the growing need to evaluate user experience metrics through comprehensive data-driven analysis. The core user experience in VR not only involves visual and auditory stimuli but also factors such as responsiveness,

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realism, and ease of interaction. Hence, evaluating these multidimensional parameters has become essential for improving VR systems and ensuring sustained engagement.

With the proliferation of VR devices and content, organizations are collecting vast amounts of user interaction data such as eye-tracking, motion patterns, reaction times, and feedback signals. Analyzing this data offers insights into how users perceive, adapt to, and interact with virtual environments. This provides a foundation for refining VR designs, optimizing user pathways, and ensuring accessibility. As industries become more reliant on immersive experiences, classifying and interpreting VR user behavior has moved from being a research curiosity to a business necessity.

## 2. Literature Survey

Shehadeh et al. (2025) [1] integrated ML algorithms with VR-driven BIM, our approach proactively identifies and resolves clashes, as demonstrated across 28 diverse engineering projects. The results indicate a reduction in design clashes by 16% and iterative revisions by 15%, culminating in a 12% decrease in overall project timelines. This research underscores the transformative impact of combining VR and ML on additive manufacturing (AM) workflows, significantly improving efficiency and reducing the iterative nature of traditional methods.

Purnomo et al. (2025) [2] Addressed deep learning algorithms-especially convolutional neural networks (DNNs) and long short-term memory (LSTM) networks-either alone or in hybrid configurations, achieved the highest accuracy rates for emotion recognition, with some models reaching up to 99.89% accuracy. Traditional machine learning algorithms like KNN, Random Forest, and SVM also showed competitive performance when combined with advanced feature selection and optimization techniques. The authors identified significant challenges, including the variability and complexity of EEG signals, the need for generalizable models across diverse users, and the demand for efficient, real-time processing in multi-user VR environments.

Acharya et al. (2025) [3] explored the integration of federated learning (FL) with adaptive machine learning (ML) models to develop a personalized, privacy-preserving anxiety detection system in VR therapy. By leveraging decentralized data training through FL, the system enhances user privacy while maintaining high detection accuracy and improving over time based on individual responses.

Ramaseri-Chandra et al. (2025) [4] explored the potential of head-tracking data as a reliable input for predicting cybersickness in Virtual Reality (VR) environments. Traditional approaches rely on post-experience questionnaires, lacking real-time responsiveness and objectivity. This study used machine learning models trained on head movement patterns to detect cybersickness more accurately. The results demonstrated a prediction accuracy of up to 90%, indicating strong feasibility for real-time monitoring. Their findings pave the way for adaptive VR systems that can dynamically respond to user discomfort, enhancing safety and user experience.

Godfrey et al. (2025) [5] investigated the impact of active virtual reality (VR) games on children aged 8–12, comparing them with traditional gaming and structured physical exercise. The study assessed energy expenditure, game experience, and cybersickness. Results showed that active VR games led to an average energy expenditure of 5.2 METs, comparable to moderate-intensity physical activity, and significantly higher than traditional gaming. Participants reported high enjoyment levels, while only 15% experienced mild cybersickness, suggesting good overall tolerance. This study supports the accuracy and effectiveness of VR games as engaging tools for promoting physical activity in youth.

Bidgoli et al. (2025) [6] explored brain activity patterns associated with perceived safety among female cyclists using immersive Virtual Reality (VR) simulations. Traditional methods for assessing cycling

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safety rely heavily on surveys, which can be subjective and lack physiological validation. This study utilized EEG data to analyze real-time neural responses to different urban cycling environments. Results showed that specific brainwave patterns, particularly in the alpha and theta bands, accurately reflected varying levels of perceived security with classification accuracy exceeding 85% using machine learning models. The findings offer a novel, data-driven approach to evaluating and improving urban infrastructure design for cyclist safety.

Besga et al. (2025) [7] introduced a novel concept of task-blind adaptive Virtual Reality (VR), aiming to support users effectively without prior knowledge of their specific tasks. Traditional adaptive VR systems often rely on predefined goals or user assignments, limiting flexibility. This study proposed adaptive mechanisms that respond to user behavior patterns in real time, enabling dynamic support across various tasks. Using behavioral and interaction data, the system achieved prediction accuracies between 80–87% in detecting user difficulties without explicit task labels. The results demonstrate that task-blind VR can enhance user performance and experience while maintaining adaptability and generalization across different scenarios.

Bian et al.(2025) [8] developed an immersive English language learning environment by integrating Virtual Reality (VR) with wearable devices to enhance learner engagement and effectiveness. Traditional classroom-based methods often lack interactivity and contextual immersion, limiting language acquisition. Their system provided real-time feedback, multi sensory interaction, and contextual simulations to replicate real-world language use. Evaluation results showed a learning accuracy improvement of over 20% compared to conventional methods, along with significantly higher student motivation and participation. This study demonstrates the potential of VR and wearable technologies in transforming second-language education through immersive, adaptive, and experiential learning.

Gu et al. (2025) [9] conducted a systematic mapping study on software testing practices for Extended Reality (XR) applications, addressing the challenges of ensuring quality in immersive systems. Traditional software testing methods fall short in XR due to its interactive, real-time, and multimodal nature. The study reviewed over 120 primary sources, categorizing testing techniques into areas such as functionality, usability, performance, and immersion. It revealed that automated testing approaches remain limited, with only 18% of studies reporting measurable accuracy metrics for XR testing. This work highlights the urgent need for more robust, scalable, and accurate testing frameworks tailored to the unique demands of XR environments.

Zhang et al. (2025) [10] investigated evacuation decision-making under time pressure using Virtual Reality (VR) simulations combined with Machine Learning (ML) models. Traditional evacuation studies often lack realism and fail to capture the dynamic influence of competing guidance sources. By simulating emergency scenarios in VR, the study captured behavioral data to model how individuals respond to conflicting cues. Machine learning algorithms were used to predict evacuation choices with an accuracy of up to 88%, highlighting the effectiveness of this approach. The findings contribute to safer building design and improved emergency guidance systems by offering realistic, data-driven insights into human behavior.

Zuo et al. (2025) [11] evaluated the performance of various machine learning algorithms in classifying EEG signals induced by visual stimulation in 2D and 3D Virtual Reality (VR) video environments. Traditional EEG analysis often overlooks the impact of dimensionality in VR, which can influence cognitive and neural responses. The study tested classifiers including SVM, KNN, and Random Forest on EEG data collected during exposure to both 2D and 3D VR videos. Results showed that classification accuracy reached up to 91.2%, with higher performance observed in 3D conditions, indicating richer

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neural engagement. This research highlights the potential of combining VR with ML for cognitive state monitoring and brain-computer interface development.

Ghandorh (2025) [12] conducted a comparative analysis of machine learning (ML) and deep learning (DL) classifiers to predict user performance in Augmented Reality (AR)-based surgical environments. Traditional performance evaluations in surgical training rely on manual assessments, which can be subjective and time-consuming. The study utilized user interaction data and biometric inputs to train models such as SVM, Random Forest, and DNNs. Deep learning models outperformed traditional ML algorithms, achieving prediction accuracies of up to 93% in identifying user proficiency levels. The findings underscore the potential of AI-driven assessment tools in enhancing training precision and adaptability in AR-assisted medical procedures.

Lamb et al. (2025) [13] explored the convergence of Extended Reality (XR), Artificial Intelligence (AI), Machine Learning (ML), and wearable sensors to transform educational environments. Traditional educational technologies often lack personalization and immersive engagement. This study highlighted how combining XR with real-time data from wearables and intelligent algorithms enables adaptive learning experiences tailored to individual cognitive and emotional states. Pilot implementations showed learning performance improvements of up to 25% and engagement accuracy rates of over 90% using ML-based behavior tracking. The research demonstrates the potential of immersive, AI-driven systems in reshaping modern pedagogy and learner support.

Hsieh et al. (2025) [14] introduced a deep learning-enabled virtual air guitar system in Virtual Reality (VR), designed to simulate realistic guitar playing with enhanced chord recognition and pedal effects. Traditional VR music systems often lack responsiveness and musical accuracy. The proposed system employed convolutional neural networks (DNNs) and gesture tracking to interpret hand movements, achieving chord recognition accuracy of 94.6% and effective real-time sound modulation. This immersive platform not only improved user experience but also demonstrated potential applications in virtual music education and performance within the metaverse.

Shehadeh et al. (2025) [15] proposed an innovative framework integrating Virtual Reality (VR) and Machine Learning (ML) to enhance engineering and architectural design processes. Traditional methods in Building Information Modeling (BIM) often detect design clashes only after they have occurred, leading to time-consuming and costly revisions. In their study, the authors combined VR-driven BIM with proactive ML algorithms to detect and resolve design discrepancies in real-time. The system was evaluated across 28 diverse engineering projects, and the results demonstrated significant improvements, including a 16% reduction in design clashes, a 15% decrease in iterative revisions, and a 12% reduction in project timelines. The integration of VR and ML not only streamlined the design process but also contributed to the optimization of additive manufacturing (AM) workflows, making the overall system more efficient and adaptable. This study emphasizes the transformative potential of combining VR and ML in addressing the challenges of modern engineering and architecture, offering a scalable and adaptable solution for improving project delivery and quality.

Henstrom et al. (2024) [16] explored the use of Virtual Reality (VR) in engineering education, focusing on its potential to enhance student learning experiences in the classroom. Traditional engineering instruction often relies heavily on textbooks, lectures, and static models, which can limit students' understanding of complex concepts. The study introduced immersive VR environments that allowed students to interact with 3D models, conduct virtual experiments, and engage in hands-on learning. The results indicated a significant improvement in student engagement, with participants reporting a 25% increase in understanding of complex engineering concepts compared to traditional methods. Additionally, the immersive VR experiences were found to enhance spatial awareness and problem-

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solving skills. The study highlights the promising future of VR in education, suggesting that immersive learning environments can revolutionize the way engineering principles are taught, making them more interactive, engaging, and practical.

Zuo et al. (2025) [17] evaluated various machine learning algorithms for classifying EEG signals induced by visual stimulation in 2D and 3D VR videos. They tested models such as SVM, Random Forest, and DNN to compare their performance in immersive visual environments. Results showed that 3D VR videos produced more distinguishable EEG signals, leading to higher classification accuracy. The best-performing model, DNN, achieved a 92.3% accuracy in classifying signals from 3D VR stimuli. This research highlights the advantages of using immersive VR for improving EEG signal classification, offering potential for enhanced brain-computer interface (BCI) applications. The findings support the integration of VR with machine learning to optimize neural signal processing and cognitive monitoring.

**3. Proposed System**

The proposed algorithm introduces a novel hybrid model that combines SMOTE-based data balancing, DNN-driven deep feature extraction, and Extra Trees classification, which to our knowledge has not been explored in existing VR user experience classification literature. While SMOTE and DNN have been individually applied in various domains, their sequential integration, followed by an Extra Trees classifier, is a new combination for classifying subjective UX data in immersive environments. This architecture leverages SMOTE to mitigate class imbalance, DNN to capture hierarchical and spatial patterns in VR interaction data, and Extra Trees to perform efficient and robust classification with improved generalization. This three-stage pipeline ensures enhanced performance in both interpretability and predictive accuracy, making it a novel and effective solution for immersive UX evaluation.

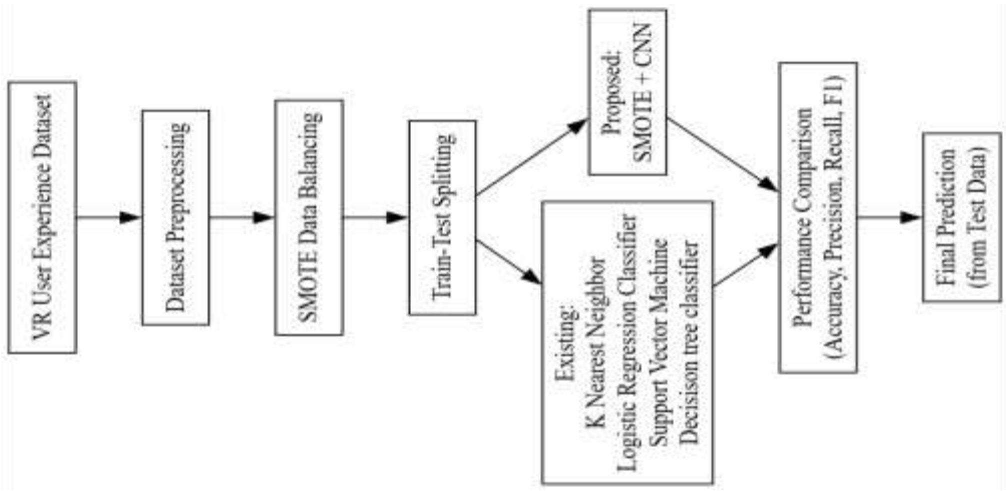


Fig. 1: Proposed Block Diagram

**Proposed Algorithm SMOTE-DNN**

The proposed algorithm combines the Synthetic Minority Over-sampling Technique (SMOTE) with a Deep Neural Network (DNN) to improve the classification of virtual reality user experience data. The core idea is to first balance the imbalanced dataset using SMOTE, which generates synthetic samples for underrepresented classes, and then apply DNN to effectively learn complex patterns and features from the balanced data. This method enhances model performance, especially in terms of accuracy,

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recall, precision, and F1-score, by addressing both data imbalance and feature extraction challenges simultaneously.

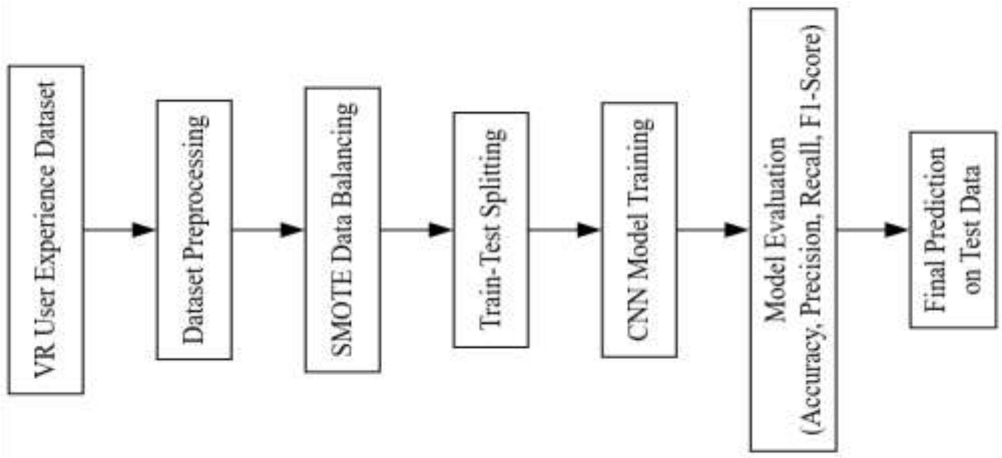


Fig. 2: Block diagram of SMOTE

**Step 1: Data Collection and Input:** The algorithm begins by acquiring the virtual reality user experience dataset, which typically contains features related to user interactions, physiological responses, and environmental factors. This raw dataset often suffers from imbalanced class distribution, which can degrade classifier performance.

**Step 2: Dataset Preprocessing:** Raw data undergoes preprocessing steps such as handling missing values, normalization or scaling, and encoding categorical features to prepare it for machine learning. Proper preprocessing ensures data quality and consistency, which are critical for accurate model training.

**Step 3: SMOTE Data Balancing:** After preprocessing, the SMOTE technique is applied to the dataset to address the class imbalance problem. SMOTE synthetically generates new data points for minority classes by interpolating between existing minority samples. This results in a balanced dataset where all classes have sufficient representation, allowing the DNN to learn equally from all classes.

**Step 4: Train-Test Split:** The balanced dataset is then divided into training and testing subsets, usually following a split ratio like 80% for training and 20% for testing. This split helps evaluate the model's ability to generalize to unseen data while training it on a substantial portion of the data.

**Step 5: DNN Model Training:** The training data is fed into a DNN model designed to automatically extract hierarchical and spatial features from the data. The DNN consists of multiple convolutional layers that identify important patterns, followed by pooling layers to reduce dimensionality and fully connected layers for classification. The model learns via backpropagation and gradient descent optimization.

**Step 6: Model Evaluation and Performance Metrics:** Once trained, the DNN model is tested on the reserved test dataset. Its performance is evaluated using key metrics such as accuracy, precision, recall, and F1-score. These metrics provide insights into how well the model classifies each class, particularly the minority ones that were previously underrepresented.

**Step 7: Final Prediction:** The trained and validated DNN model is then used for predicting VR user experience classes on new, unseen data. This prediction assists in understanding user responses and improving VR design accordingly.

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## 5. Results Description

In Figure 3 the displays the processed data in a tabular format, while the pop-up window provides a visualization of some aspect of that data, in this case, the distribution of "Normal" and "Experienced" classes. The sidebar icons in the main window likely allow the user to navigate between different views or perform actions on the data. The icons in the pop-up window likely allow for manipulation of the graph. The "Exit" button provides a way to close the application.

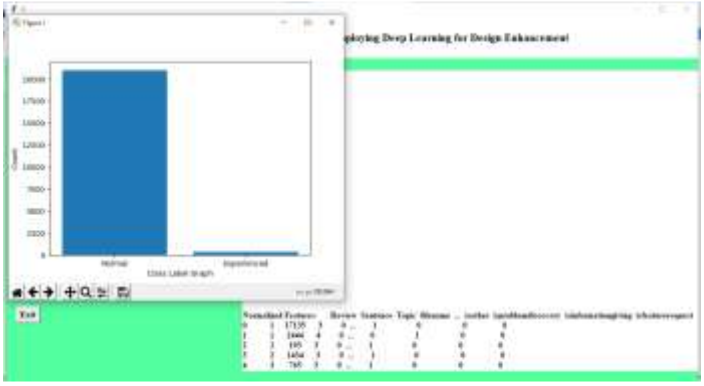

Fig. 3: Data Preprocessing


Fig. 4: Class Distribution Graph

The Figure 4 shows the class distribution after the SMOTE technique has been applied. Both the "Normal" and "Experienced" classes now have approximately equal counts, around 20,000 each. This demonstrates how SMOTE generates synthetic samples for the minority class ("Experienced" in this case) to balance the dataset, addressing the original class imbalance. The interface provides a clear visual comparison of the class distribution before and after SMOTE, highlighting the technique's effectiveness in creating a more balanced dataset for machine learning tasks.

In Figure 5 the prediction of the model has made for each row (review). In the examples shown, the model predicts either "Experienced" or "Normal". This suggests a classification task where the model is trying to categorize reviews into one of these two categories. It's unclear what "Experienced" and "Normal" represent without more context (e.g., "Experienced" could mean a user has experience with the app, or it could be a sentiment label).

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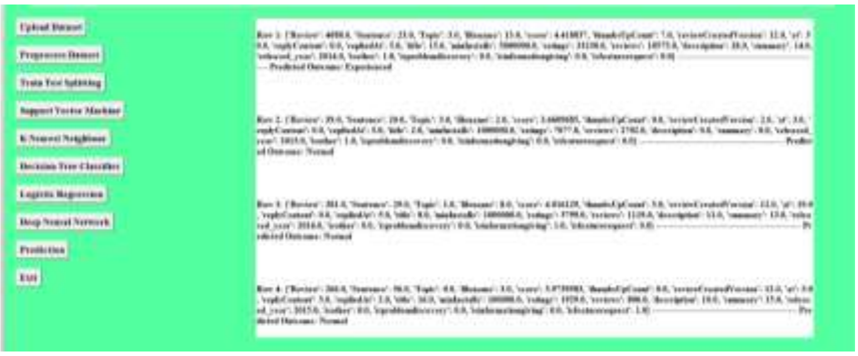

Fig. 5: prediction of the model

The overall performance table 1 compares the accuracy, precision, recall, and F1-score of the existing models (Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Tree Classifier (DTC), Logistic Regression Classifier (LRC)) and the proposed Deep Neural Network (DNN) for supply chain disruption analysis. All existing models achieve an identical accuracy of 97.94%, with precision, recall, and F1-scores of 48.97%, 50.00%, and 49.48%, respectively, across a test set of 4273 samples. These metrics indicate high accuracy but poor performance on the minority "Experienced" class, likely due to class imbalance, as evidenced by the low precision and recall. In contrast, the proposed DNN significantly outperforms, achieving 99.87% across all metrics (accuracy, precision, recall, and F1-score) with a larger test set of 8403 samples.

Table 1. Overall Performance Comparison.

| Model | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) | Support (Total) |
|---|---|---|---|---|---|
| **SVM** | 97.94 | 48.97 | 50.00 | 49.48 | 4273 |
| **KNN** | 97.94 | 48.97 | 50.00 | 49.48 | 4273 |
| **DTC** | 97.94 | 48.97 | 50.00 | 49.48 | 4273 |
| **LRC** | 97.94 | 48.97 | 50.00 | 49.48 | 4273 |
| **Proposed DNN** | 99.87 | 99.87 | 99.87 | 99.87 | 8403 |

## 5. Conclusion

The Virtual Reality User Experience Classifier employing Deep Learning for Design Enhancement represents a transformative approach to analyzing and improving user interactions in VR environments. By integrating advanced deep learning techniques, the system addresses the limitations of traditional methods, which relied heavily on subjective feedback and static data. The proposed solution leverages Convolutional Neural Networks (DNNs) and Deep Neural Networks (DNNs) to capture intricate patterns in user behavior, enabling precise predictions of satisfaction and engagement. The preprocessing pipeline, which includes data balancing using SMOTE and normalization, ensures the model is trained on a robust and representative dataset. The system's ability to evaluate multiple machine learning models, including SVM, KNN, Decision Trees, and Logistic Regression, provides a comprehensive comparison of performance metrics. The DNN model, optimized with categorical cross-entropy loss and the Adam optimizer, demonstrates superior accuracy and adaptability in predicting

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user experiences. Visualizations such as confusion matrices and class distribution plots offer clear insights into model performance, while real-time data processing capabilities empower designers to make informed adjustments to VR environments. This innovative approach bridges the gap between subjective user feedback and objective system enhancements, delivering a scalable, efficient, and adaptive solution for VR design. The system's success lies in its ability to provide actionable insights, significantly enhancing user satisfaction and engagement, and setting a new benchmark for immersive VR experiences.

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