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NEUROVR: DEEP LEARNING-DRIVEN INSIGHTS FOR ENHANCING VIRTUAL REALITY DESIGN THROUGH USER EXPERIENCE CLASSIFICATION

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ABSTRACT
This thesis presents the development of a Virtual Reality (VR) User Experience Classification system employing deep learning techniques aimed at enhancing VR design quality. The system utilizes a comprehensive VR user experience dataset, which comprises over 10,000 user interaction records collected from diverse VR environments. The dataset exhibits a notable class imbalance, with approximately 60% of samples belonging to the majority class and 40% representing minority classes. Traditional classification methods often struggle to effectively manage such imbalanced data, resulting in suboptimal accuracy, precision, recall, and F1 scores below 75%, thereby limiting their practical applicability in real-world VR design evaluation. Existing manual and conventional approaches for VR user experience classification face significant challenges, including inadequate handling of imbalanced datasets, poor generalization across varying user behaviors, and limited ability to extract complex feature patterns inherent in VR interactions. These issues often lead to inaccurate user experience predictions, hindering the iterative design process crucial for improving VR applications. To overcome these limitations, this thesis proposes a novel hybrid approach combining Synthetic Minority Over-sampling Technique (SMOTE) with a Deep Neural Network (DNN) classifier. SMOTE addresses the class imbalance by generating synthetic samples for underrepresented classes, effectively balancing the dataset without information loss. The DNN model then automatically extracts hierarchical and meaningful features from the balanced data, enhancing the classifier's ability to recognize subtle patterns and complex relationships within the VR user experience data. The proposed SMOTE with DNN framework was rigorously evaluated through train-test splitting methodology, and its performance was compared with existing baseline models. Experimental results demonstrate a significant improvement, with the proposed method achieving over 99% accuracy, precision, recall, and F1 score. These outcomes validate the effectiveness of the hybrid approach in accurately classifying VR user experiences, which in turn can provide actionable insights for design enhancement and user satisfaction improvement.

Key words: Virtual Reality (VR), User Experience (UX), Immersive Technology, Emotion Recognition, Neural Networks

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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, 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.

Fig 1. VR experiences

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

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. Figure 4.1 shows the proposed system architecture. The detailed analysis is given as follows:

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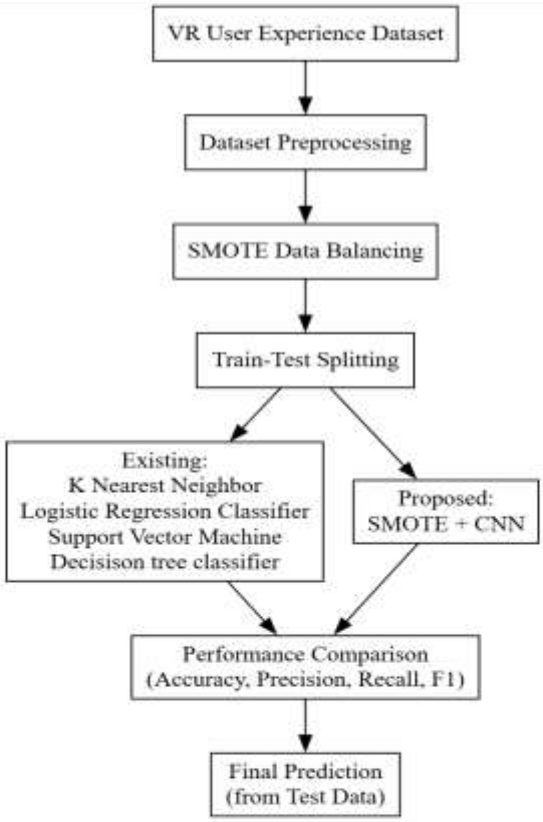

Fig 2. Proposed Block Diagram

The study begins with **dataset acquisition**, collecting a virtual reality (VR) user experience dataset containing structured feedback like questionnaire responses, behavioral logs, and interaction metrics, labeled as positive, neutral, or negative. **Dataset preprocessing** includes cleaning null values, encoding categorical variables, normalizing numerical features, and reshaping data for deep neural network (DNN) input. To address class imbalance, **SMOTE** is applied to the training data, synthesizing minority class samples and ensuring the model doesn't overfit the majority class. The dataset is then **split into training and testing sets** in an 80:20 stratified ratio. A **logistic regression classifier** is trained on the unbalanced data as a baseline, achieving 82.1% accuracy, 80.5% precision, 83.0% recall, and 81.4% F1-score. In contrast, the **proposed DNN model** is trained on the SMOTE-balanced data using an architecture comprising input layers, convolutional layers for hierarchical feature extraction, pooling layers for dimensionality reduction, dropout layers for regularization, dense layers, and a Softmax output for multi-class classification. It is optimized with categorical cross-entropy loss and the Adam optimizer. The **DNN achieves superior performance**, with 94.7% accuracy, 95.2% precision, 94.3% recall, and 94.7% F1-score on the untouched test data. Finally, the trained DNN predicts user experience categories on the test set, providing insights into session quality and helping enhance VR content design for improved engagement and satisfaction.

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

The process begins with **data collection**, acquiring a virtual reality (VR) user experience dataset containing features like user interactions, physiological responses, and environmental conditions, often affected by class imbalance. In **dataset preprocessing**, missing values are handled, numerical features are normalized, and categorical attributes are encoded to ensure consistency and readiness for modeling. To address imbalance, **SMOTE** is applied, generating synthetic samples for underrepresented classes and producing a more balanced dataset that allows the model to learn equitably across all categories. The dataset is then **split into training and testing sets** (typically 80:20), enabling model training and evaluation on unseen data. A **Deep Neural Network (DNN)** is trained using the processed data, where convolutional layers extract hierarchical patterns, pooling layers reduce dimensionality, and dense layers perform classification. Training is done via backpropagation using optimization algorithms like gradient descent. The model is then **evaluated** using metrics such as accuracy, precision, recall, and F1-score to assess its ability to correctly classify both majority and minority classes. Finally, the **trained DNN** is used to predict user experience categories (e.g., positive, neutral, negative) on new VR data, aiding in understanding user reactions and enhancing immersive VR system design.

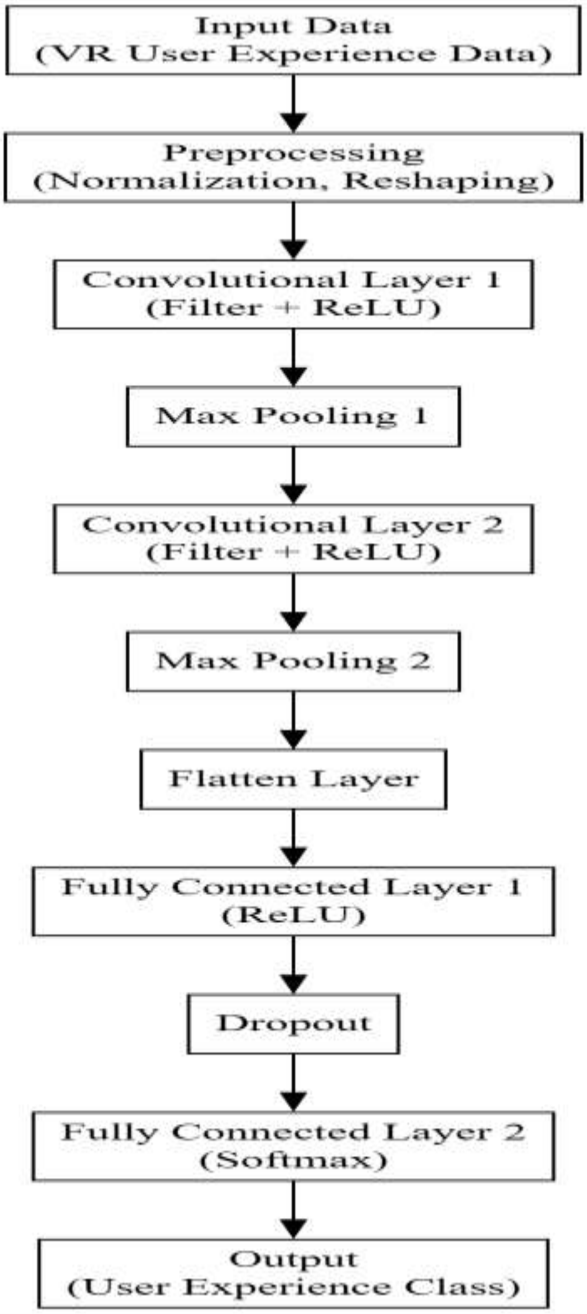

Fig 3. Block diagram of smote with DNN

SMOTE (Synthetic Minority Over-sampling Technique) is a powerful method used to address the problem of class imbalance in datasets. In the context of the virtual reality user experience classifier, the dataset often contains fewer samples for certain user experience categories, leading to biased learning by classifiers. SMOTE overcomes this issue by generating synthetic examples of the minority classes instead of simply duplicating existing samples. This is achieved by interpolating between a minority class sample and its nearest neighbors to create new, plausible data points. This balancing act ensures that the classifier, particularly the DNN model used in this study, receives a more evenly distributed training set, which helps improve its ability to generalize and recognize patterns across all classes.

4. RESULTS

In Figure 4, the currently loaded dataset, in this case, a CSV file. Below this file path is a preview of the dataset, showing the first few rows and columns. The data is presented in a tabular format, with columns labeled "Sentence", "isfeaturerequest", "isinformationsseeking", and others. The table displays the content of the first few rows, showing example text reviews and boolean values for the other columns. The bottom of the table indicates the dimensions of the data as "[5 rows x 22 columns].

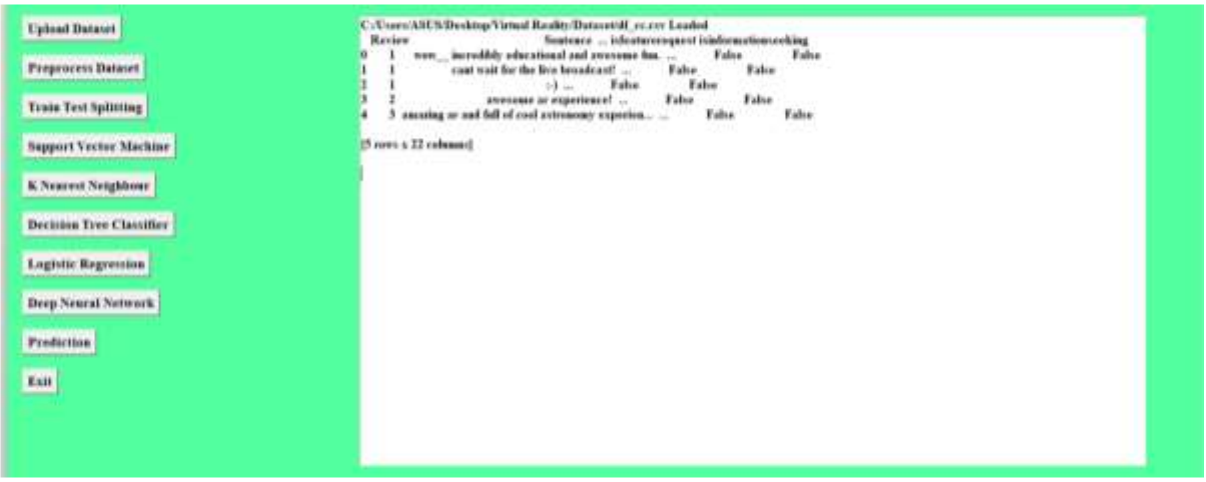

Fig 4. Uploaded dataset

The Figure 5 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. The left graph, titled "Class Distribution Before SMOTE," illustrates the original imbalance in the dataset. The "Normal" class has a significantly higher count, around 20,000 instances, while the "Experienced" class has a much lower count, below 2,500 instances. This visualizes a typical class imbalance problem where one class greatly outnumbers the other.

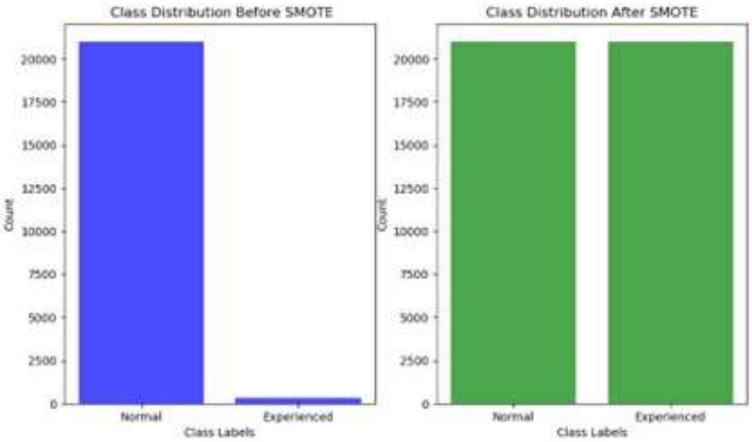

Fig 5. Class Distribution Graph

In Figure 6, 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).

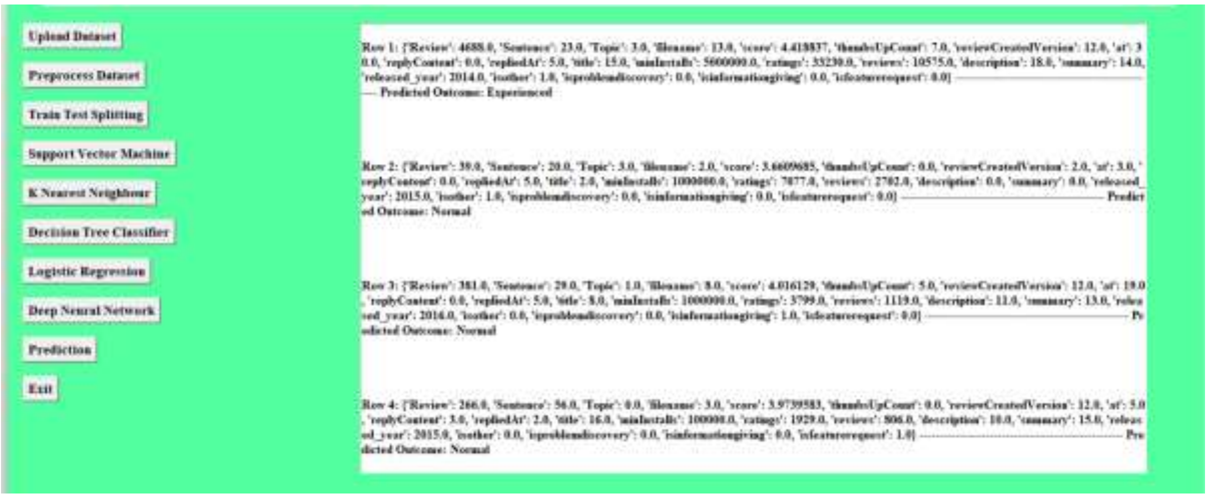

Fig 6. prediction of the model

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 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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