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N.V. HUNG, N.A. QUAN, N. TAN, T.T. HAI, D.K. TRUNG, L.M. NAM, B.T. LOAN, N.T.T. NGA

BUILDING PREDICTIVE SMELL MODELS FOR VIRTUAL REALITY ENVIRONMENTS

Nguyen Viet Hung, Nguyen Anh Quan, Nguyen Tan, Tran Trieu Hai, Dang Khanh Trung, Le Mai Nam, Bui Thanh Loan, Nguyen Thi Thuy Nga. **Building Predictive Smell Models for Virtual Reality Environments.**

Abstract. In a sensory-rich environment, human experiences are shaped by the complex interplay of multiple senses. However, digital interactions predominantly engage visual and auditory modalities, leaving other sensory channels, such as olfaction, largely unutilized. Virtual Reality (VR) technology holds significant potential for addressing this limitation by incorporating a wider range of sensory inputs to create more immersive experiences. This study introduces a novel approach for integrating olfactory stimuli into VR environments through the development of predictive odor models, termed SPRF (Sensory Predictive Response Framework). The objective is to enhance the sensory dimension of VR by tailoring scent stimuli to specific content and context with the collection of information about the location of scent sources and their identification through features to serve to reproduce them in the space of the VR environment, thereby enriching user engagement and immersion. Additionally, the research investigates the influence of various scent-related factors on user perception and behavior in VR, aiming to develop predictive models optimized for olfactory integration. Empirical evaluations demonstrate that the SPRF model achieves superior performance, with an accuracy of 98.13%, significantly outperforming conventional models such as Convolutional Neural Networks (CNN, 79.46%), Long Short-Term Memory (LSTM, 80.37%), and Support Vector Machines (SVM, 85.24%). Additionally, SPRF delivers notable improvements in F1-scores (13.05%-21.38%) and accuracy (12.89%-18.67%) compared to these alternatives. These findings highlight the efficacy of SPRF in advancing olfactory integration within VR, offering actionable insights for the design of multisensory digital environments.

Keywords: virtual reality, odor, model selection, user experience, imagination, odor prediction.

1. Introduction. The rapid expansion of virtual worlds and advancements in 3D space technology have ushered in a new era of human interaction and perception. As research in these fields progresses, the integration of virtual environments with real-life experiences becomes increasingly significant [1]. This evolution reflects a growing interest in enhancing human vision and creating immersive experiences that bridge the gap between virtual and real worlds. Consequently, there is a concerted effort to explore how these developments can enrich human life and foster a future characterized by greater enjoyment and connectivity [2].

Moreover, today's multisensory digital experiences have enhanced human interaction with technology, with the aim of replicating real-world sensory perceptions. The objective is to integrate human senses into digital environments, creating a seamless and immersive experience. However, delivering a comprehensive sensory digital experience poses significant challenges due to various influencing factors. This endeavor is prioritized in the future technological development [3]. Current digital techniques often lack full auditory stimulation and integration with other senses, which presents a major challenge in increasing consumer value [4]. Besides, the future expansion of VR systems has captured the keen interest of researchers, making studies on transmission and prediction increasingly essential. In particular, the ability to predict and simulate odors in virtual environments is expected to play a pivotal role, especially in enhancing the online transmission of 360-degree videos [5-7]. This area of research is not only necessary but also holds immense potential to revolutionize immersive experiences in the future.

The integration of olfactory elements into virtual reality (VR) environments marks a groundbreaking advancement in immersive technology, addressing a sensory dimension that has traditionally been overlooked in digital spaces. Olfaction, with its profound influence on human perception, memory, and emotion, offers significant potential to enhance user immersion and realism in virtual environments. Recent technological advancements have enabled the incorporation of scents into VR, thereby providing a more holistic sensory experience. While much of the recent research in VR has focused on areas such as viewport position prediction and the evaluation of 360-degree video streaming quality [8-11], studies on integrating olfactory stimuli into VR remain limited. However, predictive modeling, as demonstrated in studies such as [9, 10], plays a critical role in enhancing VR experiences by anticipating user interactions and optimizing immersion. Building on these advancements, this work seeks to enhance user perception in virtual environments by combining predictive modeling with engaging olfactory stimuli. By doing so, we aim to create a novel and immersive virtual atmosphere that deepens realism and enriches the overall user experience.

The proposed scent recognition system in virtual reality works by collecting and analyzing scents in the surrounding space through customized electronic noses integrated directly under the virtual reality glasses with gas sensors used in the e-nose such as MP503, BME680, MQ3, MQ5, MQ9 and WSP2110 it is shown in Figure 1. When the user wears the glasses, these electronic noses continuously scan the environment, detecting and collecting scent molecules in the air. The collected data is then processed by advanced algorithms to classify the scent, identify the characteristics of the scent, and accurately predict the distance from the source to the location of the VR glasses. The system also takes into account environmental factors that may affect the diffusion of scents, such as wind speed and direction, temperature, humidity, and air quality. As a result, the algorithm can calibrate parameters to ensure that the prediction of the scent's location is simulated as accurately as possible. When a scent source is detected, the system displays or recreates its location in the virtual reality environment, providing the user with a more realistic experience. With this technology, users in virtual reality environments can not only see and hear but also intuitively perceive scents, opening up many potential applications in the fields of entertainment, education, scientific research and even environmental investigation.

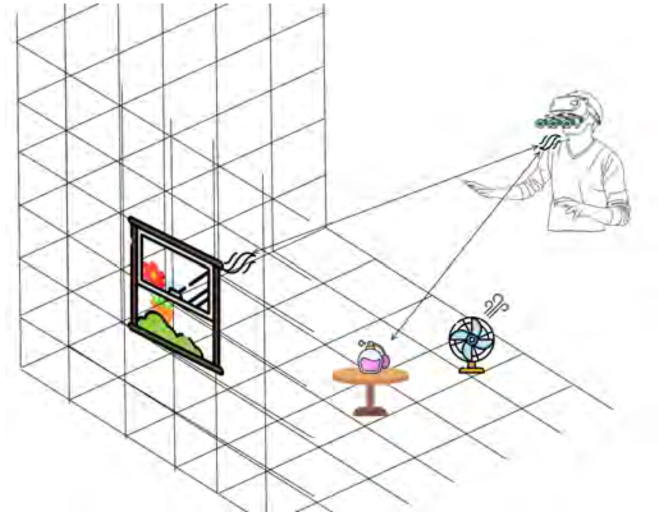

Fig. 1. System in a virtual reality environment

Predictive odor models are at the forefront of this innovation, providing the ability to simulate realistic olfactory experiences using complex algorithms and extensive scent databases. These models work by analyzing the chemical compositions of odors and predicting their perceptual attributes, thereby enhancing the realism and interactivity of VR applications. Such applications span diverse fields, including gaming, education, therapeutic interventions, and marketing strategies.

Figure 2 shows an architectural model for developing predictive odor systems in virtual reality environments. It features four key layers. The Data Collection Layer collects information through sensors and odor data repositories. Moving to the Processing Layer, chemical analysis is conducted alongside machine learning models, such as Support Vector Machines (SVM), to predict odor perceptions. The Integration Layer ensures seamless connectivity between VR software and olfactory display systems, enabling the emission of odors within virtual environments. Finally, the User-Interaction Layer focuses on incorporating feedback mechanisms and user interfaces to refine and enhance user experiences. The flow between these layers is depicted with arrows, illustrating the sequential process from data collection to user interaction.

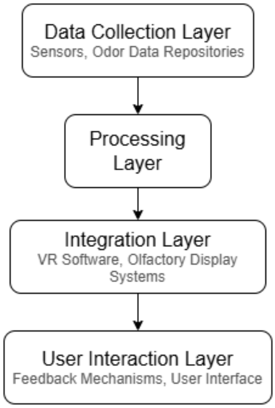

Fig. 2. Architectural model for predictive odor models in VR

The novelty of predictive odor models lies in their scientific approach to synthesizing and delivering scents with precision. Using machine learning techniques and comprehensive olfactory research, these models can accurately reproduce a broad spectrum of odors. This capability is pivotal in overcoming the challenges associated with creating consistent and repeatable olfactory experiences in VR, ensuring that users receive reliable sensory input regardless of the context.

On the one hand, predictive odor models facilitate the creation of personalized and adaptive scent experiences, representing a significant leap toward user-centric virtual environments. By tailoring scent profiles to individual preferences or specific VR scenarios, these models enable a level of customization that was previously unattainable. This personalization not only enhances user engagement but also allows for the exploration of new dimensions in digital interaction.

In addition to improving user experience, predictive odor models have significant potential to advance research on the human olfactory system and its influence on behavior and cognition. By simulating diverse scent scenarios, researchers can investigate psychological and physiological responses to different odors within controlled virtual settings. This research can lead to a deeper understanding of the interplay between olfaction and various cognitive processes.

Ultimately, the development of predictive odor models represents a substantial leap forward in the pursuit of truly immersive virtual realities. As technology continues to evolve, these models will play an essential role in bridging the gap between the virtual and the real, providing users with a multisensory experience that closely mirrors real-world interactions. This advancement not only enriches the sensory landscape of VR but also opens new avenues for innovation across multiple disciplines.

2. Related work. The development of predictive odor models for virtual reality (VR) environments is a multidisciplinary endeavor that integrates insights from olfactory science, computational modeling, and immersive technology. This field has gained traction due to the increasing demand for more immersive VR experiences that engage multiple senses beyond sight and sound. Researchers have explored various approaches to simulate and predict olfactory experiences, with the aim of enhancing realism and user engagement.

Early work in olfactory science laid the groundwork by identifying the fundamental properties of odors and how they are perceived by humans. Studies such as those by the authors in [12] on olfactory receptors provided crucial insights into how humans detect and differentiate odors. This understanding is vital for creating models that can predict how different odorants will interact and be perceived in a virtual space.

In computational modeling, efforts have been made to simulate odor dispersion in virtual environments. These models often draw on fluid dynamics to predict how odor molecules move and spread. For example, the research by the authors in [13] applied computational fluid dynamics (CFD) to model odor dispersion in enclosed spaces, which can be adapted for VR scenarios. Such models help to create realistic odor propagation in virtual worlds, accounting for factors such as air flow and temperature.

Machine learning techniques have also been used to improve predictive accuracy. By training algorithms on large data sets of odorant molecules and their perceived smells, researchers aim to predict olfactory experiences more reliably. Approaches using neural networks, as discussed in [14, 15], show promise in predicting odor characteristics based on molecular structure, which is crucial for VR applications where real-time processing is needed.

In the realm of immersive technology, the integration of olfactory feedback into VR systems presents unique challenges. Devices such as scent diffusers and wearable olfactory interfaces have been developed to deliver controlled odor stimuli. The research by the authors in [16] demonstrated how olfactory stimuli could be synchronized with visual and auditory cues to enhance the sense of presence in VR. This synchronization is key to creating a cohesive and believable virtual environment.

Furthermore, user experience studies are crucial to understanding how predictive odor models affect immersion and enjoyment in VR. Experiments often involve user testing to evaluate the effectiveness of olfactory integration. Findings from studies such as those by the authors in [17] suggest that olfactory signals can significantly enhance the perception of presence and emotional impact in virtual settings.

The challenge of standardization and calibration of olfactory devices remains a critical area of research. Differences in individual perception and the subjective nature of smell require models and devices to be highly adaptable. Collaborative efforts, such as those led by ISO working groups, aim to establish guidelines and standards for olfactory VR implementations, ensuring consistency and reliability across different systems.

Privacy and ethical considerations are emerging concerns as VR environments become more personalized. The collection and processing of olfactory data raises questions about user consent and data security. Researchers such as the authors in [18] emphasize the need for ethical frameworks to address these issues, ensuring that advances in olfactory VR respect user privacy.

Recent advances in sensor technology also play a pivotal role in the development of predictive odor models. The miniaturization and increased sensitivity of electronic noses enable more precise detection and analysis of odorants in real time. Studies by the authors in [19] highlight the potential of these sensors in VR applications, where they can provide feedback loops to dynamically adjust the virtual olfactory environment.

In summary, the development of predictive odor models for VR environments is a rapidly evolving field that bridges several scientific and technological domains. Continued research and collaboration across these areas will be essential to overcome current limitations and unlock the full potential of immersive olfactory experiences. As technology matures, it holds the promise of creating truly multisensory virtual worlds that can transform entertainment, education, and training.

In this study [20], machine learning-based classification models were developed to predict odor characteristics using the psychophysical data set created by the authors. This data set includes data on odorant properties for 480 structurally diverse compounds, each measured at two different concentrations (dilutions).

This study [21] uses data from five reservoirs in Kansas, USA, to create predictive models that relate dissolved geosmin concentrations to water quality factors. Individual reservoir-based models outperformed pooled data models in terms of performance. Events related to taste and smell occurred outside of the summer, and wintertime saw higher amounts of geosmin. The development of universal models was hampered by the strong dependence of geosmin concentrations on regional environmental conditions. Inorganic phosphorus limits have been found to play a major role in controlling the generation and release of geosmin into the water column.

This study [22] uses comprehensive data on a variety of biotic and abiotic characteristics of Taihu Lake to create predictive models for T&O (Taste and Odor) chemicals. The realistic dynamics of the T&O compounds were accurately recorded and a good match was achieved. They took into account two algal growth seasons (blooming and non-blooming) and two fractions of the T&O compounds (dissolved and particle bound), in contrast to previous odor models. The models proved to be useful for water resource managers in anticipating the possibility of T&O accidents and showed a high degree of accuracy in predicting T&O concentrations.

Due to the wider applicability and efficiency of model-based aroma design in SOR (Stimulus-Organism-Response) creation, this study [23] used it. In order to precisely characterize the olfactory characteristics and facilitate the creation of a more potent SOR, R-profile descriptors were utilized. Furthermore, the SOR was modeled using Machine Learning (ML) based on Artificial Neural Network (ANN), which demonstrates the accuracy of the model with an average R^2 of 0.8807. Two case studies, aroma replacement and odor tuning, validated by tests and literature, supported the efficacy of the ML model and the computer-aided aroma design framework (CAAD) for aroma mixtures.

This study [24] presents a predictive model to predict chemical odor characteristics represented by binary values from mass spectra. The predictive model incorporates the language modeling approach Word2vec. The similarity between descriptors is minimized because, in the Sigma-Aldrich catalog data utilized in this work, descriptors representing the olfactory characteristics of molecules are used solely, even when additional descriptors express comparable odor characters.

Laboratory data were used in this study [25]. However, Internet of Things (IoT) sensor devices are used to gather information regarding odor compounds in real-world livestock scenarios. Due to the nature of data collection using sensors, missing data for a variety of causes is a frequent problem.

This study [26] uses dynamic olfactometry and analytical techniques to examine gas emissions from nine solid wastes and digestates during the active composting phase. The authors measured 22 important odorants and correlated them with odor concentration (OC) using an odor activity value (OAV) approach based on odor detection thresholds (ODT). To forecast OC trends, linear models employing OAVmax and OAVsum, as well as partial least squares (PLS) regressions, were investigated. Outperforming OAVmax and OAVsum, the PLS model explained 74-76% of the variance in OC. The important causes of odor pollution were found to be key odorants such as dimethyl sulfide, methanethiol, and hydrogen sulfide. In order to verify whether the PLS model can be applied to other processes, the validation set must be expanded.

3. Methodology

3.1. Introduction to Methodology. Odor recognition in virtual reality (VR) environments is an interdisciplinary research field that combines sensory science and machine learning to create realistic olfactory experiences. Machine learning models such as Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), Support Vector Machines (SVM), and Random Forests play an important role in processing and analyzing complex odor-related data. Each model has its own advantages, but not all are suitable for the current research objectives and conditions. After careful consideration, we chose Random Forest as the primary method to conduct this research and created a model named the Sensory Predictive Response Framework (SPRF).

CNN is a powerful model for processing spatial data, such as images or chemical structures. However, the main drawback of CNN is that it requires a large amount of data for training. This is a major challenge in the field of odor research, where data is often limited and difficult to collect. LSTM, with its ability to analyze temporal data and detect long-term dependence patterns, is also a potential option, but it requires high computational resources and considerable time for parameter optimization, which is not suitable for the scale of this study. Meanwhile, SVM has advantages in classifying data at high spatial scales, but when dealing with large or complex data sets, SVM is prone to becoming inefficient and resource-consuming.

Based on the current methodologies, a new model needed to be developed, and SPRF was chosen by us because it better fits the current research goals and context. The SPRF model is described in Section 4. It is a decision tree-based machine learning method distinguished by its ability to handle incomplete, noisy, and multidimensional data. It is particularly useful in early studies where olfactory data is often incomplete or non-normilized. A significant strength is its ability to perform well on small to medium-sized datasets and provide interpretable results. This allows us to analyze and adjust the model more flexibly during the research process.

Additionally, SPRF offers a balance between accuracy and performance. Unlike deep models such as CNNs or LSTMs in [27], it does not require high hardware configurations or complex optimization techniques. With the ability to synthesize multiple decision trees, it not only reduces the risk of overfitting but also improves confidence in predictions. These characteristics make it an ideal method for performing initial analyses in the prediction of odor, laying the foundation for further research and practical applications in VR.

3.2. Research Design. In this section, we describe the type of research 3.2.1 and specifically outline our research design 3.2.2.

3.2.1. Type of research. Both qualitative and quantitative methodologies are used in this investigation. Specifically, in this study, qualitative factors are presented through the analysis of human sensory responses to odors in a virtual reality (VR) environment, in order to better understand the interaction between olfactory sensation and environmental factors. Quantitative factors, on the other hand, are applied in the analysis of data collected from sensors (e-nose), helping to determine the relationship between the chemical characteristics of odors and the recorded sensory characteristics.

3.2.2. Description of research design.

– **Data Collection**. Data were collected from experiments with subjects (68 people) in a controlled environment. Important parameters such as phi (azimuth) and theta (tilt angle) were recorded from electronic sensors, and the data were stored as text files (txt) containing odor information. At the same time, participants' sensory responses to odors were recorded as color values in the CIELAB color space, allowing for the analysis of the relationship between odors and colors. In addition, using CIELAB allows for better representation of nonlinear data because gas sensors measure the concentration of compounds in the air, and the data obtained is often nonlinear. If using a color space such as RGB, the values may overlap making it difficult to distinguish between odors.

– **Experimental Design**. In a virtual reality environment, participants were exposed to different odors, such as black pepper, caramel, and cherry. The experiments were designed so that participants were not distracted and could concentrate on odor recognition under controlled environmental conditions. Environmental parameters such as light and temperature were also maintained and kept stable throughout the experiment.

– **Survey and data analysis**. After collecting sensory and chemical data, we use data analysis methods to model the relationship between odors and sensory features (color). Machine learning models are applied, including regression, sliding windows, and data normalization, to analyze the collected data. Specifically, we use the sliding-window analysis method to generate consecutive data sequences, which enables the machine learning model to predict odors based on chemical and sensory features.

– **Model evaluation**. Machine learning models are evaluated using metrics such as the root mean square error (RMSE) to test the accuracy of predictions. The data is divided into training and testing sets to determine the generalizability of the model and test the reliability of the results.

– **Analysis of results**. Finally, the results obtained from the machine learning models will be compared with previous studies, and the validity of the data will be checked. The results from the experiments and models will provide insights into how odors are recognized in virtual reality environments, thereby helping to improve odor prediction models in future research.

3.3. Data Collection. In this section, we present the prediction of odor in virtual reality spaces. The environment plays a crucial role, as it encompasses the simulated settings where scents are integrated to enhance immersiveness. Participants are individuals who engage with these virtual environments, providing feedback on their sensory experiences to help refine odor prediction models. The data set comprises data collected from these interactions, including sensory responses and environmental variables, which are analyzed to improve the accuracy of odor predictions in digital simulations.

We use the dataset from [28], which is used to predict the color associated with odors using an electronic nose (e-nose). Perceptual data was collected from 68 participants who were asked to associate colors with ten different odors such as black pepper, caramel, and cherry. These participants selected colors in the CIELAB color space, which includes three channels: L* for lightness, a* for the red-green axis, and b* for the yellow-blue axis. The odors were presented in a controlled environment to ensure consistent lighting conditions.

On the one hand, the chemical data was obtained using a custom-made e-nose equipped with various gas sensors, such as MP503, BME680, and MQ9. This setup allowed for the extraction of chemical features from the odors, which were then used to train the regression models. The e-nose recorded 100 samples, ten for each odor, with sensors that capture data on air quality, pollution level, and other environmental factors. The data were pre-processed by averaging sensor responses and smoothing signals before being used in the analysis.

On the other hand, the final dataset consisted of ten features per sample, excluding the time component used for packet reordering. Regression models were trained to predict the L*, a*, and b* values for each odor based on the chemical characteristics captured by the e-nose.

The odor data in this study were collected in large datasets consisting of ten odors, each stored in ten data files. As shown in Figure 3, these files serve as examples for the remaining ten odors in the dataset and are depicted as two 3D graphs.

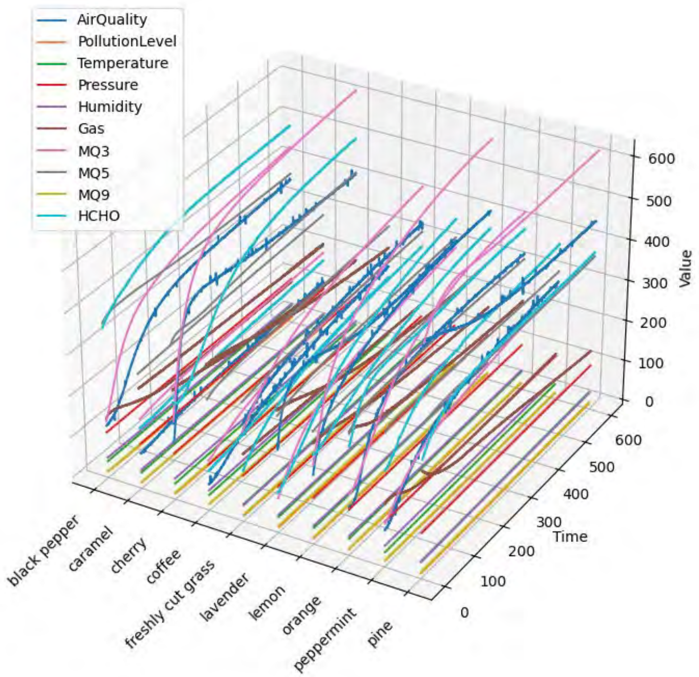

Fig. 3. Analyzed Scent Data from Sensors

As mentioned above, each collected odor dataset contains eleven columns of data describing that odor, as detailed below.

– **Time** is responsible for allocating time during the data collection process.

– **AirQuality** is responsible for measuring and evaluating air quality based on parameters such as fine dust concentration (PM2.5, PM10) and toxic gases.

– **PollutionLevel** measures the concentration of air pollution in the environment.

– **Temperature** measures the current ambient temperature, expressed in °C or °F units.

– **Pressure** measures atmospheric pressure, commonly used for weather and environmental conditions analysis, in hPa or mmHg.

– **Humidity** measures the relative humidity of the air, expressed as a percentage (%).

– **Gas** measures the concentration of flammable or toxic gases in the air, such as methane (CH4) or carbon monoxide (CO).

– **MQ3** sensor detects alcohol vapor, mainly for measuring ethanol concentration in the air.

– **MQ5** sensor is used to measure gases such as LPG, methane and butane.

– **MQ9** sensor detects carbon monoxide (CO) and other flammable gases in the air.

– **HCHO** measures the concentration of formaldehyde (HCHO), a pollutant commonly found in indoor or industrial environments.

Thus, a collected odor has ten collection files, and each file can have approximately 2125 rows of collected data with eleven columns. The recording process is done continuously, and the collected values are updated in real time. This ensures that even smallest change in the environment is accurately recorded by the "e-nose".

3.4. Data Analysis. In this study, data analysis was mainly performed using Python, a programming language with development tools such as PyCharm for coding and data processing. Popular libraries such as NumPy and Pandas were used for data manipulation and processing, while machine learning models were built and evaluated with the support of libraries such as Scikit-learn and Keras. Below are two sections related to data processing: the first is Data Analysis Methodology 3.4.1, which analyzes the data in this study, including various techniques for processing and understanding the data, and the next is Data Reliability and Validity Check 3.4.2. Through the above techniques, we can ensure that the collected data is accurate, reliable, and highly valid, thereby laying a solid foundation for the machine learning model in predicting odors in virtual reality environments.

3.4.1. Data Analysis Methodology.

– **Descriptive Statistics**. Before building the model, the data is explored through descriptive statistical techniques such as calculating the mean, standard deviation, and distribution of the values. This helps to identify key features of the data, such as *phi* and *theta* values, and detect outliers that may affect the model results.

– **Data transformation**. To ensure that the data falls within a suitable range for the machine learning model, normalization techniques are applied. The *transform* function is used to normalize the data, bringing the *phi* and *theta* values to a range of *0* to *1*, which helps to increase the accuracy and performance of the model.

– **Regression**. To predict phi and theta values, regression models are used, in which linear regression techniques or more complex models such as Gaussian Process Regression (GPR) can be applied to analyze the relationship between chemical characteristics and sensory values.

– **Sliding window analysis**. An important technique used in this study is sliding window analysis, which aims to generate consecutive data sequences to serve as input to the machine learning model. Sliding window functions help to divide the data into consecutive sub-segments, providing training samples for the regression model. This technique helps the model to learn the temporal features in phi and theta data over time.

3.4.2. Data Reliability and Validity Check.

– **Reliability**. To check the reliability of the data, we use methods such as dividing the data into training and testing sets. This helps to evaluate the generalization ability of the model and confirm that the model does not overfit the training data. The results of the model are measured by metrics such as root mean square error (RMSE), which helps to assess the accuracy of the predictive model.

– **Validity**. The validity of the data is checked by comparing it with experimental results or previous studies in the field. The data is collected from reliable sources and under strictly controlled conditions, ensuring that outliers do not affect the results. Furthermore, the data is thoroughly processed to remove missing or unusual values that may cause bias in the analysis.

4. Experiments

4.1. Experimental Settings. In this part, we will install and test the Python programming language on a 64-bit Windows 11 Pro computer. The system specifications include a Core i5-6300U processor, 16GB of RAM, a 512GB SSD, and a 12.5-inch HD display with a resolution of 1366x768. Additionaly, we conducted data analysis and created graphs using the Python programming language, focusing on a dataset comprising 11 features collected from odor samples [28]. These samples were instrumental in developing odor prediction models, which paved the way for future research involving a broader range of odors. This expansion is crucial for improving the accuracy and applicability of our models.

To support these advancements, we plan to incorporate assessments in complex 3D spaces using virtual reality. These environments provide objective evaluations for participants, enhancing their experience and ensuring more rigorous testing conditions. This approach will facilitate the development of more robust and versatile odor prediction models.

An overview of our research model is presented in Figure 4. This model is designed to predict scent in virtual reality (VR) environments using the Random Forest algorithm. The model-building process includes many important steps, from input data collection, processing and feature extraction, to training and evaluating prediction performance.

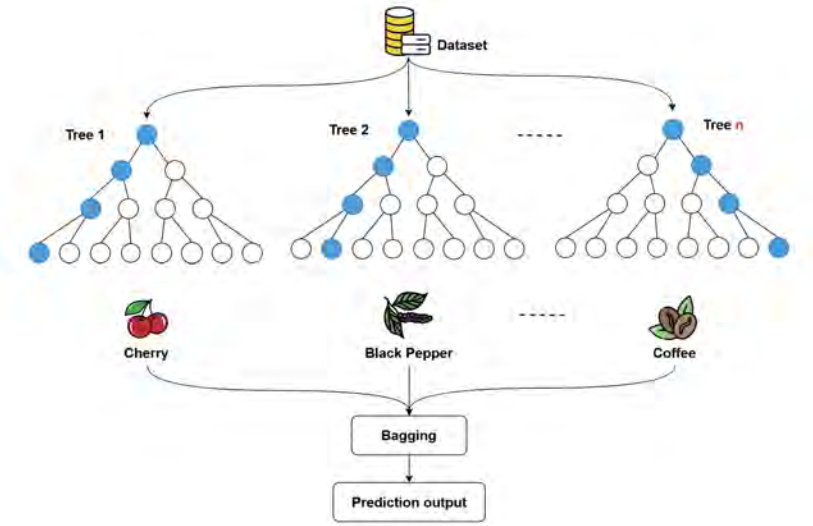

Fig. 4. Model Overview

Bootstrap Sampling. For each tree T_i, a subset $\mathscr{D}_i$ is randomly sampled from the training dataset $\mathscr{D}$, with the size equal to that of $\mathscr{D}$ but allowing repetition. The mathematical formulation of this sampling process is given by Equation (1). In this, the index j_k is drawn randomly from the set of available data points, as defined in Equation (2) below:

$$\mathscr{D}_i = \{x_{j_1}, x_{j_2}, \ldots, x_{j_m}\}, \quad \text{where } x_{j_k} \in \mathscr{D}, \tag{1}$$

where:

– $\mathscr{D}_i$ – bootstrap sample for the i-th tree.

– x_{j_k} – the k-th data point sampled from the dataset $\mathscr{D}$.

– $\mathscr{D}$ – the training dataset.

$$m = |\mathscr{D}| \quad \text{and } j_k \sim \text{Uniform}(1, m), \tag{2}$$

where:

– m – the total number of data points in the training set $\mathscr{D}$.
– j_k – randomly drawn index for the k-th data point.
– $\text{Uniform}(1, m)$ – random sampling from the set $\{1, 2, \dots, m\}$.

Building Each Decision Tree. Each tree T_i is constructed based on $\mathscr{D}_i$, with several random features. At each split node, a random subset $\mathscr{F}$ of features n is considered to select the best-split point. The size of $\mathscr{F}$ is typically $\sqrt{n}$ or $\log_2(n)$.

The Gini index, given in Equation (3), is used to evaluate the quality of each potential split. This index helps determine how well the split divides the data into distinct classes. The lower the Gini index, the purer the split.

$$G = 1 - \sum_{k=1}^{K} p_k^2, \tag{3}$$

where:

– G – the Gini index for a given split.
– K – the number of classes (labels).
– p_k – the probability of a sample belonging to class k at that node.

Aggregating the Results. After building N decision trees, the algorithm aggregates the results from all the trees to make a prediction. For classification problems, the final prediction $\hat{y}$ is obtained by taking the class that appears most frequently across all trees, as shown in Equation (4).

$$\hat{y} = \arg\max_k \left(\sum_{i=1}^{N} \mathbb{I}[T_i(x) = k] \right), \tag{4}$$

where:

– $\hat{y}$ – the predicted class label.
– k – a class label.
– $T_i(x)$ – the prediction made by the i-th tree for input sample x.
– $\mathbb{I}[\cdot]$ – indicator function (1 if the condition is true, 0 if false).
– N – the total number of trees in the forest.

For regression problems, the final prediction is the average of all the individual tree predictions, as seen in Equation (5).

$$\hat{y} = \frac{1}{N}\sum_{i=1}^{N} T_i(x), \tag{5}$$

where:

– $\hat{y}$ – the predicted value for regression.

– $T_i(x)$ – the output of the i-th tree for input sample x.

– N – the total number of trees in the forest.

Specific Parameters from Code.

– Number of trees ($n\_estimators$): $N = 100$. Increasing the number of trees N helps reduce the model's variance but increases training and prediction time.

– Random feature subset size at each node ($\mathscr{F}$). By default in sklearn, $\mathscr{F} = \sqrt{n}$, where $n = 11$, so $\mathscr{F} \approx 3$.

– Maximum depth (max_depth): ∞ (default). Allows the tree to grow until leaf nodes achieve purity ($Gini = 0$).

– Minimum samples to split a node ($min\_samples\_split$): 2.

– Minimum samples at each leaf node ($min\_samples\_leaf$): 1.

– Bootstrap sampling. Used to ensure that each tree is built from a different dataset.

4.2. Performance Analysis. In the realm of machine learning, performance analysis is essential to evaluate how well different models meet the objectives of a given task. Therefore, by understanding the strengths and limitations of various algorithms, such as CNN [29], LSTM [30], and SVM [31] and the proposed (SPRF), we can make informed decisions on model selection and optimization. In this part, we delve into the comparative performance of these models, providing insights into their applicability to diverse datasets and problem domains.

In this research area, we evaluate the performance of a prediction model using accuracy as a key metric. Accuracy is defined as the ratio of correct predictions to the total number of predictions. It is calculated using the following formula:

$$Accuracy = \frac{NumberofCorrectPredictions}{TotalNumberofPredictions}. \tag{6}$$

Next, F1-Score is used as an important evaluation metric in various types of tasks to evaluate the performance of a model because it combines precision and recall scores:

$$recall = \frac{TP}{TP + FN}, \tag{7}$$

$$precision = \frac{TP}{TP + FP}, \tag{8}$$

$$F1 - Score = \frac{2 \times precision \times recall}{precision + recall}, \tag{9}$$

where:

– TP. The number of times the model correctly predicted a scent that actually existed.

– TN. The number of times the model correctly predicted that a scent did not exist and that scent did not exist.

– FP. The number of times the model incorrectly predicted that a scent existed but did not exist.

This metric provides a straightforward assessment of the model's effectiveness in making accurate predictions.

Table 1 presents a comparative analysis of model accuracy metrics for four different machine learning models: CNN [29], LSTM [30], SVM [31], and SPRF. The accuracy percentages indicate the performance of each model in terms of its ability to correctly predict outcomes. The CNN model, with an accuracy of 79.46%, was the least accurate among the models presented, given that they used CNN for odor pleasantness prediction. While CNNs are typically strong in handling image data due to their convolutional layers, their lower performance here might suggest that the dataset used is not well-suited for a CNN's architecture, or that the model was not optimally tuned. This highlights the importance of model selection and hyperparameter tuning in achieving high accuracy.

Table 1. Comparative Analysis of Model Accuracy Metrics

Models	Accuracy (%)	F1-Score (%)
CNN [29]	*79.46*	*76.70*
LSTM [30]	*80.37*	*77.70*
SVM [31]	*85.24*	*85.03*
The proposed (SPRF)	***98.13***	***98.08***

The LSTM model showed a slightly better accuracy of 80.37%, which represents a modest improvement over CNN, but their LSTM was built with automatic gas source localization in an outdoor environment in mind. They set the feature transformation function in the convolutional layer to ⟨3,3,5⟩ with no padding. LSTMs are particularly effective in handling sequential data, such as time series or natural language processing tasks. The marginal increase in accuracy suggests that the data set may have some sequential aspect, but the improvement is not substantial. This could mean that the LSTM architecture captures some temporal dependencies better than CNN but still struggles to fully understand the underlying patterns, possibly due to insufficient data preprocessing or feature engineering.

On the one hand, the SPRF model that we developed – previously no Random Forests model has been applied to predict smells in virtual reality environment – achieved a significantly higher accuracy of 98.13%, making it the most accurate model in this comparison. Random Forests are ensemble learning methods that are robust to overfitting and can handle a wide variety of data types, which might explain their superior performance. This suggests that the dataset features are well-suited for decision tree-based models, where feature importance and interactions play a crucial role. The high accuracy of the SPRF model implies that it effectively captures the complex patterns within the data, making it a reliable choice for similar datasets.

On the other hand, the Support Vector Machine (SVM) model also performed well, with an accuracy of 85.24%. SVM has not been applied to odor recognition in virtual environments; it has been used for emotion recognition in VR scenes [31] and some other VR-related categories such as odor source localization [32] so we further developed the SVM model to apply to odor prediction to provide more model choices for odor prediction in this study and demonstrated that SPRF performs well, SVMs are known for their effectiveness in high-dimensional spaces and are especially useful in classification tasks with clear boundary distances. The performance of the SVM model shows that it can handle the data efficiently, although not as well as the SPRF model. This shows that although SVM can delineate classes to a good extent, it may not capture all complex patterns as effectively as the ensemble approach of the SPRF model.

In conclusion, the data indicate that the model selection should be tailored to the characteristics of the data set. The Random Forest model outperforms the others, suggesting its suitability for these particular data. However, the choice between models should also consider other factors such as computational efficiency, interpretability, and specific application requirements. The results emphasize the importance of understanding the strengths and limitations of each model type, as well as the necessity for a thorough data analysis to guide model selection and optimization.

4.3. Discussing Smell in VR Environment. To integrate odor sensor models into the VR system, first, it is necessary to collect data from odor and gas sensors, then use data analysis algorithms to convert the measured values into signals that can be interacted with in the VR environment. Sensors such as MQ3, MQ5, and HCHO [33] will provide data on specific gases, while the data processing system will analyze and reproduce odors in the virtual space.

System installation requires connecting VR software to sensors via data transmission protocols, such as MQTT or WebSocket [34, 35], to ensure that sensor data are continuously updated and responded to promptly. VR software will need to integrate biological models and odor analysis to create realistic odor responses in the virtual environment. The odor generation system will be installed to reproduce odors based on sensor data while ensuring stability and high performance when operating in the VR environment.

This process requires both software and hardware to work in sync, with the VR software controlling and simulating the environment, and the hardware performing the odor reproduction.

Potential issues that may arise during this process:

– *Accuracy of sensor data.* Odor and gas sensors need to be highly accurate to ensure that the data collected is accurate and reliable in simulations. If the collected data is skewed or inaccurate, this can lead to incorrect odor reproduction or even negative effects in the simulation.

– *Interaction between odors and the VR environment.* One of the major challenges in integrating odor sensors into VR is how to make the odors perceived realistically and in line with other elements in the virtual environment. This requires a sophisticated system that can combine odors with other elements such as images, sounds, and sensations in the VR space.

– *Odor technology in virtual environments.* To create a realistic experience, the odor system must be able to reproduce odors with high accuracy and be adjustable. However, this technology still faces some limitations in the ability to reproduce various odors, the consistency of the odors over time, and the precision of the odor distribution in virtual space.

5. Conclusions. In conclusion, based on empirical research, the SPRF smell prediction outperforms other models, achieving 98.13% accuracy. In contrast, the CNN model has the lowest accuracy at 79.46%, followed by LSTM at 80.37% and SVM at 85.24%. This shows that SPRF is the most effective model for developing predictive odor models in VR environments. It improves the F1 score by 13.05% to 21.38% and accuracy by 12.89% to 18.67%. Based on these results, future research should prioritize the refinement of the SPRF model to further enhance its predictive capabilities. Furthermore, exploring hybrid models that combine the strengths of multiple approaches could lead to even more robust solutions. Implementing these advanced models will be crucial in integrating scents into VR, thus enriching digital experiences and making them more immersive and engaging.

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Nguyen Viet Hung — Lecturer, International training and cooperation institute, East Asia University of Technology. Research interests: multimedia communications, network security, artificial intelligence, traffic engineering in next-generation networks, QoE/QoS guarantee for network services, green networking, applications. The number of publications — 23. hungnv@eaut.edu.vn; Ky Phu – Ky Anh, Ha Tinh, Viet Nam; office phone: +84(098)911-2079.

Nguyen Anh Quan — Research assistant, East Asia University of Technology. Research interests: natural language processing, computer vision. The number of publications — 3. anhq46724@gmail.com; Duong Ha – Gia Lam, Hanoi, Viet Nam; office phone: +84(096)278-4293.

Nguyen Tan — Research assistant, East Asia University of Technology. Research interests: applications, data analysis. The number of publications — 4. tan25102000@gmail.com; Trung Dung – Tien Lu, Hung Yen, Viet Nam; office phone: +84(035)919-0216.

Tran Trieu Hai — Research assistant, Faculty of general education, Hanoi Open University. Research interests: network security, AI, natural language processing, applications. The number of publications — 2. haitt@hou.edu.vn; Nguyen Hien Street, Hai Ba Trung District, Hanoi, Viet Nam; office phone: +84(098)596-6866.

Dang Khanh Trung — Lecturer, Faculty of information technology, East Asia University of Technology. Research interests: multimedia communications, database management systems, artificial intelligence, applications. The number of publications — 2. trungdk@eaut.edu.vn; 14, Bo De – Long Bien, Hanoi, Viet Nam; office phone: +84(032)889-9334.

Le Mai Nam — Lecturer, Faculty of information technology, East Asia University of Technology. Research interests: software engineering, optimization mathematics, applications. The number of publications — 2. namlm@eaut.edu.vn; Phuong Trung – Thanh Oai, Hanoi, Viet Nam; office phone: +84(098)208-2117.

Bui Thanh Loan — Lecturer, Faculty of information technology, East Asia University of Technology. Research interests: multimedia communications, database management systems, artificial intelligence, applications. The number of publications — 1. loanbt@eaut.edu.vn; Long Bien, Hanoi, Viet Nam; office phone: +84(090)218-1085.

Nguyen Thi Thuy Nga — Lecturer, Faculty of information technology, East Asia University of Technology. Research interests: multimedia communications, database management systems, artificial intelligence, applications. The number of publications — 4. ngantt@eaut.edu.vn; Ta Thanh Oai – Thanh Tri, Hanoi, Viet Nam; office phone: +84(097)529-4770.

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Н.В. Хунг, Н.А. Куан, Н. Тан, Т.Т. Хай, Д.Т. Чунг, Л.М. Нам, Б.Т. Лоан, Н.Т. Нга

СОЗДАНИЕ ПРОГНОЗИРУЮЩИХ МОДЕЛЕЙ ЗАПАХОВ ДЛЯ СРЕД ВИРТУАЛЬНОЙ РЕАЛЬНОСТИ

Хунг Н.В., Куан Н.А., Тан Н., Хай Т.Т., Чунг Д.Т., Нам Л.М., Лоан Б.Т., Нга Н.Т. **Создание прогнозирующих моделей запахов для сред виртуальной реальности.**

Аннотация. В среде, насыщенной сенсорными стимулами, человеческий опыт формируется за счет сложного взаимодействия множества чувств. Однако при цифровом взаимодействии задействуются преимущественно зрительные и слуховые модальности, в то время как другие сенсорные каналы, такие как обоняние, остаются практически неиспользованными. Технология виртуальной реальности обладает значительным потенциалом для преодоления этого ограничения за счет включения более широкого спектра сенсорных стимулов, что позволяет создавать более погружающий опыт. В данном исследовании представлен новый подход к интеграции обонятельных стимулов в виртуальную среду посредством разработки прогностической модели запахов, названной Сенсорно-Прогностическая Реакционная Структура (SPRF). Цель исследования заключается в улучшении сенсорного измерения виртуальной реальности путем адаптации обонятельных стимулов к конкретному контенту и контексту. Это достигается за счет сбора информации о местоположении источников запахов и их идентификации по характерным признакам, что позволяет воспроизводить их в пространстве виртуальной среды, тем самым повышая вовлеченность и уровень погружения пользователя. Кроме того, в исследовании изучается влияние различных факторов, связанных с запахами, на восприятие и поведение пользователя в виртуальной реальности, с целью разработки прогностических моделей, оптимизированных для интеграции обонятельных стимулов. Эмпирические оценки показывают, что модель SPRF демонстрирует производительность с точностью 98,13%, значительно превосходя обычные модели, такие как сверточные нейронные сети (CNN, 79,46%), сети с долгой краткосрочной памятью (LSTM, 80,37%) и метод опорных векторов (SVM, 85,24%). Кроме того, SPRF обеспечивает заметные улучшения в показателях F1 (на 13,05%-21,38%) и точности (на 12,89%-18,67%) по сравнению с этими альтернативными моделями. Эти результаты подчеркивают эффективность SPRF в развитии интеграции обонятельных стимулов в виртуальной реальности, предлагая ценные идеи для проектирования мультисенсорных цифровых сред.

Ключевые слова: виртуальная реальность, запах, выбор модели, пользовательский опыт, воображение, прогнозирование запахов.

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Хунг Нгуен Вьет — преподаватель, международный институт подготовки кадров и сотрудничества, Восточноазиатский технологический университет. Область научных интересов: мультимедийные коммуникации, сетевая безопасность, искусственный интеллект, организация трафика в сетях нового поколения, гарантия качества сетевых услуг, экологичные сети, приложения. Число научных публикаций — 23. hungnv@eaut.edu.vn; Ки Фу – Ки Ань, Хатинь, Вьетнам; р.т.: +84(098)911-2079.

Куан Нгуен Ань — научный сотрудник, Восточноазиатский технологический университет. Область научных интересов: обработка естественного языка, компьютерное зрение. Число научных публикаций — 3. anhq46724@gmail.com; Зялам, Ханой, Вьетнам; р.т.: +84(096)278-4293.

Тан Нгуен — научный сотрудник, Восточноазиатский технологический университет. Область научных интересов: приложения, анализ данных. Число научных публикаций — 4. tan25102000@gmail.com; Чынг Зунг – Тиен Лу, Хынгйен, Вьетнам; р.т.: +84(035)919-0216.

Хай Тран Триеу — научный сотрудник, факультет общего образования, Ханойский открытый университет. Область научных интересов: сетевая безопасность, искусственный интеллект, обработка естественного языка, приложения. Число научных публикаций — 2. haitt@hou.edu.vn; улица Нгуен Хьен, район Хай Ба Трунг, Ханой, Вьетнам; р.т.: +84(098)596-6866.

Чунг Данг Тхань — преподаватель, факультет информационных технологий, Восточноазиатский технологический университет. Область научных интересов: мультимедийные коммуникации, системы управления базами данных, искусственный интеллект, приложения. Число научных публикаций — 2. trungdk@eaut.edu.vn; Бо Де – Лонг Бьен, 14, Ханой, Вьетнам; р.т.: +84(032)889-9334.

Нам Ле Май — преподаватель, факультет информационных технологий, Восточноазиатский технологический университет. Область научных интересов: разработка программного обеспечения, математика оптимизации, прикладные программы. Число научных публикаций — 2. namlm@eaut.edu.vn; Фуонг Чунг – Тхань Оай, Ханой, Вьетнам; р.т.: +84(098)208-2117.

Лоан Буй Тхань — преподаватель, факультет информационных технологий, Восточноазиатский технологический университет. Область научных интересов: мультимедийные коммуникации, системы управления базами данных, искусственный интеллект, приложения. Число научных публикаций — 1. loanbt@eaut.edu.vn; Лонг Бьен, Ханой, Вьетнам; р.т.: +84(090)218-1085.

Нга Нгуен Тхи Туй — преподаватель, факультет информационных технологий, Восточноазиатский технологический университет. Область научных интересов: мультимедийные коммуникации, системы управления базами данных, искусственный интеллект, приложения. Число научных публикаций — 4. ngantt@eaut.edu.vn; Та Тхань Оай, Тханьчи, Ханой, Вьетнам; р.т.: +84(097)529-4770.