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Exploring post-concussion vestibular disorders: A retrospective analysis using machine learning approaches

Explorando trastornos vestibulares posconmoción cerebral: un análisis retrospectivo utilizando enfoques de aprendizaje automático

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Abstract

Introduction: Post-concussion vestibular disorders significantly impact patients' quality of life, but their complex nature challenges traditional clinical assessments. **Objective:** To employ machine learning techniques to analyze vestibular disorders in post-concussion patients and describe patient behavior in the otoneurological field. **Material and Methods:** This retrospective study examined 75 post-concussion patients in Chile. Random Forest, XGBoost, and Support Vector Regression (SVR) models explored relationships between clinical characteristics and symptom duration. Data included demographic information, concussion details, symptom characteristics, and otoneurological examination results. **Results:** SVR demonstrated superior performance (RMSE 151.24), followed by XGBoost (RMSE 224.06) and Random Forest (RMSE 407.99). Key predictors included general health status, sex, and specific vestibular conditions. Vestibulovisual symptoms and specific types of benign paroxysmal positional vertigo (BPPV) emerged as significant factors. Bilateral vestibular hypofunction (BVH) alone did not significantly affect symptom duration. The analysis revealed complex interactions between clinical features and recovery time. **Conclusion:** These findings provide insights into the multifaceted nature of post-concussion vestibular disorders and highlight the potential of machine learning in enhancing our understanding of patient trajectories. Results suggest the need for comprehensive evaluation and individualized treatment approaches, potentially leading to improved risk stratification and more targeted interventions for patients with post-concussion vestibular disorders.

Keywords: Machine learning, concussion, vestibular symptoms.

Resumen

Introducción: *Los trastornos vestibulares posconmoción cerebral impactan significativamente la calidad de vida de los pacientes, pero su naturaleza compleja desafía las evaluaciones clínicas tradicionales.* ***Objetivo:*** *Emplear técnicas de "Machine Learning" para analizar trastornos vestibulares en pacientes posconmoción cerebral y describir el comportamiento del paciente en el campo otoneurológico.* ***Material y Métodos:*** *Este estudio retrospectivo examinó 75 pacientes posconmoción cerebral en Chile. Se utilizaron modelos de Random Forest, XGBoost y Regresión de Vectores de Soporte (SVR) para explorar relaciones entre características clínicas y duración de los síntomas. Los datos incluyeron información demográfica, detalles de la conmoción, características de los síntomas y resultados de exámenes otoneurológicos.* ***Resultados:*** *SVR demostró un rendimiento superior (RMSE 151.24), seguido por XGBoost (RMSE 224.06) y Random Forest (RMSE 407.99). Los predictores clave incluyeron el estado de salud general, sexo y condiciones vestibulares específicas. Los síntomas vestibulovisuales y tipos específicos de vértigo posicional paroxístico benigno (VPPB) emergieron como factores significativos. La hipofunción vestibular bilateral (HVB) por sí sola no afectó significativamente la duración de los síntomas. El análisis reveló interacciones complejas entre características clínicas y*

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tiempo de recuperación. ***Conclusión:*** *Estos hallazgos proporcionan información sobre la naturaleza multifacética de los trastornos vestibulares posconmoción cerebral y destacan el potencial del aprendizaje automático para mejorar nuestra comprensión de las trayectorias de los pacientes. Los resultados sugieren la necesidad de una evaluación integral y enfoques de tratamiento individualizados, potencialmente conduciendo a una mejor estratificación del riesgo e intervenciones más específicas para pacientes con trastornos vestibulares posconmoción cerebral.*

Palabras clave: *aprendizaje automático, conmoción encefálica, síntomas vestibulares.*

Introduction

Concussion, a form of mild traumatic brain injury (mTBI), has gained increasing attention in both clinical practice and research due to its prevalence and potential long-term consequences. While often considered a transient condition, concussions can lead to persistent symptoms[1], including vestibular disorders, which significantly impact patients' quality of life[2,3]. Vestibular disorders following concussion affect the complex system responsible for maintaining balance, spatial orientation, and stable vision during head movement. These disorders can manifest as dizziness, vertigo, balance problems, and visual disturbances[3].

The vestibular system, comprising the peripheral vestibular organs in the inner ear and central vestibular pathways in the brain, is particularly vulnerable to concussive forces. Damage to this system can result in various disorders, including Benign Paroxysmal Positional Vertigo (BPPV), vestibular migraine, and more diffuse vestibular dysfunction[4]. Understanding the nature and course of these disorders is crucial for effective management and rehabilitation of post-concussion patients.

Despite the growing recognition of vestibular disorders following concussion, their diagnosis and management remain challenging. Current challenges include the heterogeneity of symptoms[5,6], overlap with other post-concussion sequelae, and the lack of standardized assessment protocols specific to post-concussion vestibular disorders. Additionally, the variability in recovery trajectories and the potential for long-term persistence of symptoms complicate prognostication and treatment planning. Traditional clinical assessments may not fully capture the complex interplay of factors influencing vestibular symptoms post-concussion[5-7], highlighting the need for more sophisticated analytical approaches. This study addresses these challenges by leveraging machine learning techniques to uncover patterns and predictors that may not be apparent through conventional analysis methods.

Accurate diagnosis and characterization of post-concussion vestibular disorders are paramount for several reasons. Firstly, vestibular symptoms can significantly prolong recovery time and increase the risk of chronic post-concussion syndrome[1,8,9]. Secondly, different vestibular disorders require distinct treatment approaches. For instance, BPPV is treated with specific repositioning maneuvers, while more diffuse vestibular dysfunction may require a comprehensive vestibular rehabilitation program[3,10].

Machine learning techniques have shown considerable promise in improving diagnostic accuracy and prognostication in various medical fields. These methods can identify complex patterns and relationships in clinical data that may not be apparent through traditional statistical analyses or clinical intuition[11]. In the context of post-concussion vestibular disorders, machine learning could potentially identify subtle patterns in symptom presentation and clinical test results that are indicative of specific vestibular disorders[12], predict recovery trajectories based on initial presentation and early clinical course, and uncover previously unrecognized relationships between clinical features and outcomes.

Recent studies have demonstrated the utility of machine learning in concussion diagnosis and prognosis. For instance, Vergara et al. (2021)[13] used machine learning algorithms to predict recovery time in concussion patients based on early clinical features, achieving high accuracy. However, the application of machine learning techniques specifically to post-concussion vestibular disorders remains largely unexplored. Even considering other vestibular disorders, for example, Wang et al. (2024)[12] demonstrated the use of differentiation between vestibular migraine and Meniere disease to assist in diagnosis.

Objective

This study aims to address this gap by employing machine learning approaches to analyze a retrospective dataset of post-concussion patients with vestibular symptoms. Specifically, we aim to explore relationships between *clinical features, vestibular test results, and symptom duration* in post-concussion patients. Identify key predictors of prolonged vestibular symptoms following concussion. Compare the *effectiveness* of different machine learning models (Random Forest, XGBoost, and Support Vector Regression) in analyzing post-concussion vestibular data. Describe patient behavior patterns and symptom progression in the otoneurological field following a concussion. Generate insights that could inform more targeted assessment and treatment strategies for post-concussion vestibular disorders. By leveraging machine learning techniques on a retrospective dataset, we hope to uncover nuanced relationships and patterns that can enhance our understanding of post-concussion vestibular disorders and ultimately improve patient care.

Materials and Methods

Study Design and Participants

This retrospective study examined data from post-concussion patients treated at a specialized otoneurology clinic at Instituto de Neurorrehabilitación y Balance, Chile, between January 2018 and December 2022. Patients without previous vestibular disorder diagnoses were included if they had a concussion diagnosis based on established guidelines (McCrory et al., 2017)[2] and presented with vestibular symptoms. Exclusion criteria encompassed pre-existing vestibular disorders, severe traumatic brain injury, and incomplete medical records. This study was conducted following the Declaration of Helsinki. All patients provided written informed consent for using their clinical data in research. All data were de-identified and anonymized to ensure patient privacy and confidentiality before analysis.

Data Collection

Information was extracted from electronic medical records for each patient, including demographic data, concussion details, symptom characteristics, symptom duration (Evolution days) (**Figure 1**), otoneurological examination results (**Figure 2**), and specific vestibular disorder diagnoses (**Figure 3**). All patients underwent a comprehensive otoneurological evaluation (**Figure 2**), which included audiometry conducted in a soundproof chamber, impedance testing, Video Nystagmography (VNG) that included caloric test, Vestibular Evoked Myogenic Potentials (VEMPs) air conduction(Interacoustic VO425b), and Video Head Impulse Test (vHIT), model EyeSee Cam 1.1. Audiometry and impedance testing were performed using Interacoustics models (AD 629 and AT 235). VNG included testing for spontaneous nystagmus with and without ocular fixation, horizontal slow phase tracking, saccadic movements, positional tests, and caloric testing. Both cervical (cVEMP) and ocular (oVEMP) were performed using air conduction stimuli.

Diagnostic Criteria and Providers

Patients were initially referred to the center by general practitioners or other specialists. Upon admission, all patients were evaluated by a single otolaryngologist who conducted the clinical examination, ordered otoneurological testing, and made diagnoses based on the Bárány Society guidelines. The criteria for diagnosing Unilateral Vestibular Hypofunction (UVH), Bilateral Vestibular Hypofunction (BVH), and Benign Paroxysmal Positional Vertigo (BPPV) strictly adhered to these guidelines[14-16], **Figure 3** provides a detailed visualization of the diagnostic frequencies among the study cohort. Magnetic Resonance Imaging (MRI) scans were performed based on the patient's clinical presentation.

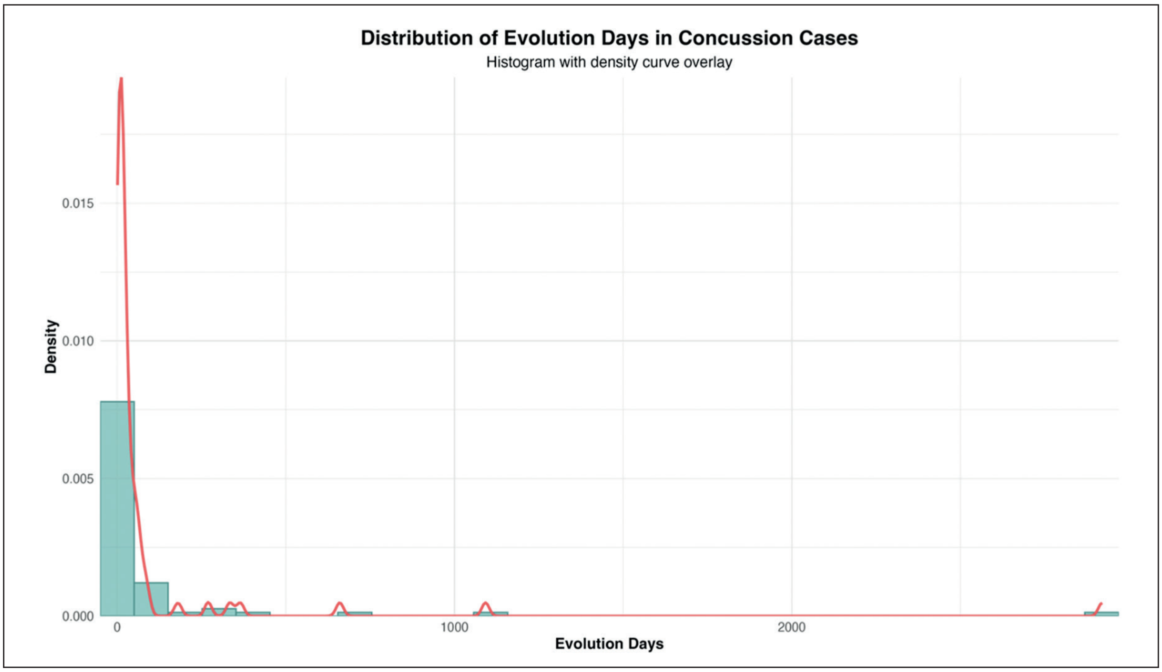

Figure 1. Distribution of Symptom Duration in Post-Concussion Patients. This histogram illustrates the distribution of symptom duration (evolution days) among 75 post-concussion patients with vestibular disorders. The x-axis represents the number of days, while the y-axis shows the frequency of patients. The right-skewed distribution indicates that while most patients experienced shorter symptom durations, a subset of patients had prolonged symptoms, with some cases extending beyond 500 days.

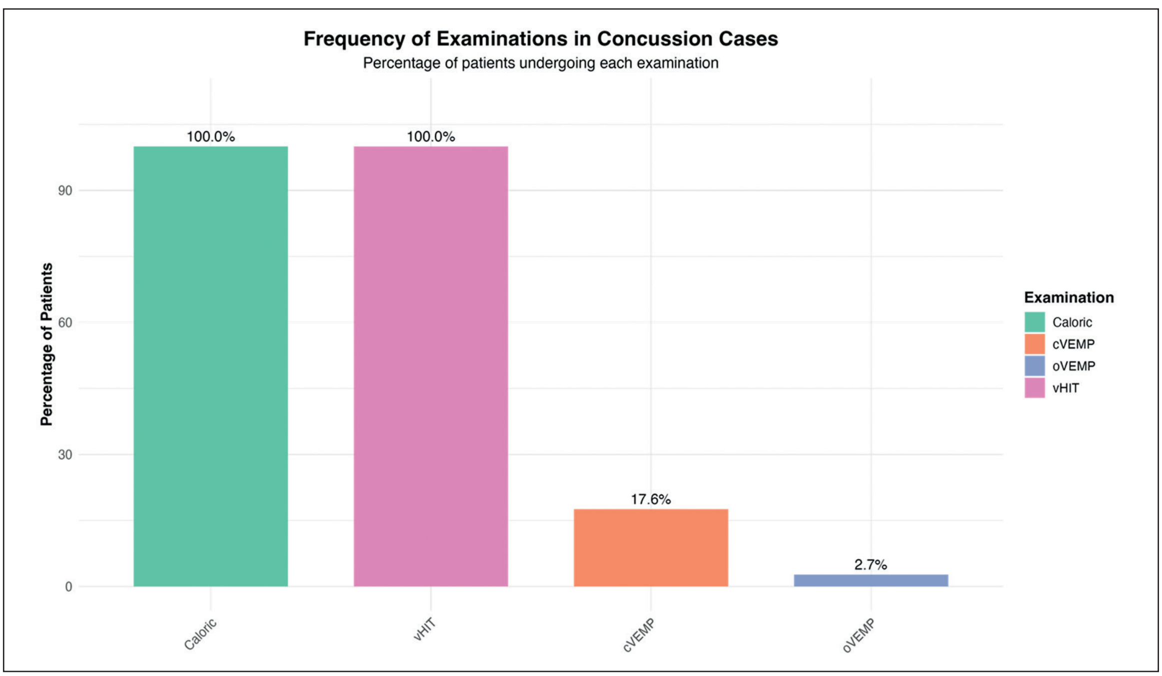

Figure 2. Frequency of Otoneurological Examinations in Post-Concussion Cases. This bar chart displays the percentage of patients who underwent various otoneurological examinations. Examinations include Video Head Impulse Test (vHIT), caloric testing, ocular Vestibular Evoked Myogenic Potential (oVEMP), and cervical Vestibular Evoked Myogenic Potential (cVEMP). The chart highlights the comprehensive assessment approach used in evaluating post-concussion vestibular disorders.

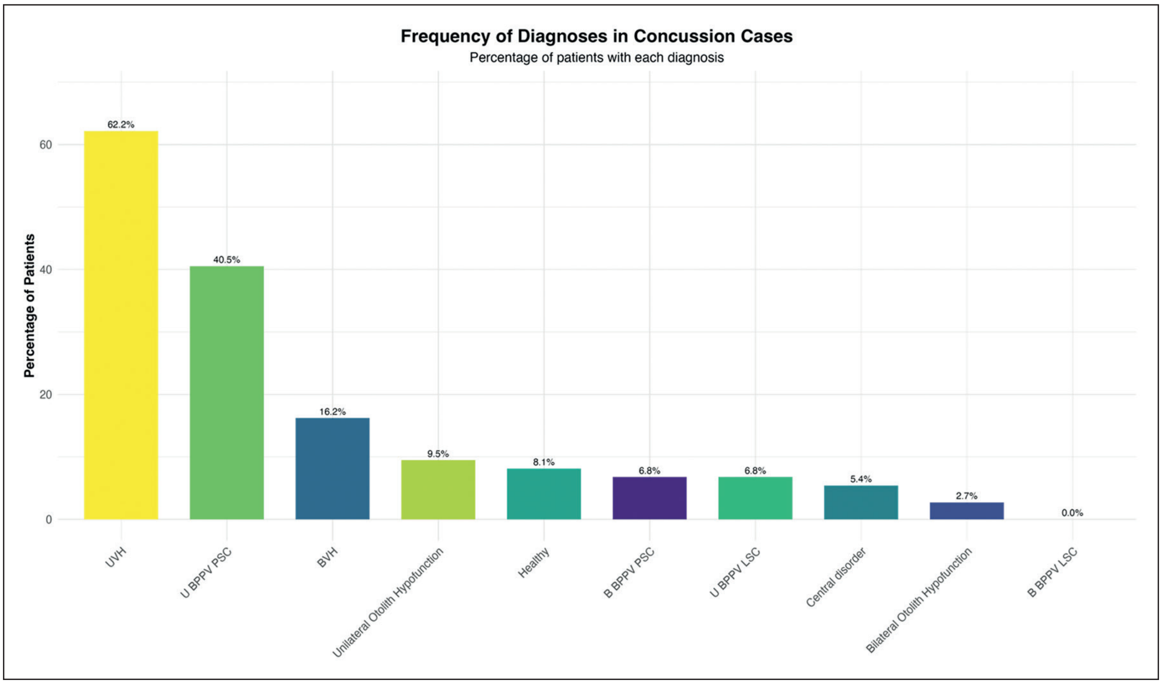

Figure 3. Prevalence of Vestibular Diagnoses in Post-Concussion Patients. This bar graph shows the frequency of specific vestibular disorder diagnoses among the study cohort.The chart illustrates the diverse range of vestibular disorders observed in post-concussion patients, with UVH and BPPV being the most common.UVH: Unilateral vestibular hypofunction; U BPPV PSC: Unilateral Benign paroxysmal positional vertigo posterior semicircular canal; BVH: Bilateral vestibular hypofunction; U BPPV LSC: Unilateral Benign paroxysmal positional vertigo Lateral semicircular canals; B BPPV LSC: Bilateral Benign paroxysmal positional vertigo Lateral semicircular canals.

Data Preprocessing

Raw data underwent several preprocessing steps to prepare for machine learning analysis. Missing data were imputed using multiple imputations by chained equations (MICE)[17], chosen for their ability to handle mixed data types and preserve variable relationships. Categorical variables were encoded using one-hot encoding to avoid introducing artificial ordinal relationships. Numerical features were standardized to ensure equal contribution to the models and prevent scale-based domination. Feature selection involved a combination of correlation analysis and domain expertise. Features with high multicollinearity (correlation coefficient > 0.8) were identified, and one feature from each highly correlated pair was retained based on clinical relevance. Features with near-zero variance were removed to reduce dataset noise.

The Interquartile Range (IQR) method was used to identify potential outliers. Values that fell outside 1.5 times the IQR were subjected to a meticulous and thorough examination. After consultation with clinical experts, outliers deemed valid extreme cases were retained in the dataset. At the same time, those resulting from data entry errors were corrected or removed if the correct value could not be determined.

Machine Learning Models

Three machine learning models were employed: Random Forest, XGBoost, and Support Vector Regression (SVR). Random Forest, an ensemble learning method constructing multiple decision trees, was chosen for its ability to handle non-linear relationships and provide feature importance scores[18]. XGBoost, a gradient-boosting algorithm, was selected for its efficiency in handling imbalanced datasets and robust performance across various problem types[19]. SVR, a regression version of Support Vector Machines, was chosen for its effectiveness in high-dimensional spaces and its ability to model complex relationships using kernel functions[20].

Model Training and Evaluation

The dataset was split into training (70%) and testing (30%) sets using stratified sampling to ensure a similar distribution of the target variable (Evolution days). Models were trained using 10-fold cross-validation on the training set to optimize hyperparameters. Grid search was employed to find optimal hyperparameters for each model, with the search space defined based on domain knowledge and computational constraints.

Model performance was primarily assessed using Root Mean Square Error (RMSE) to predict symptom duration. Feature importance scores from Random Forest and XGBoost models were analyzed to identify key predictors. For SVR, the importance of permutation was employed to assess feature relevance.

Statistical Analysis

Traditional statistical analyses complemented the machine learning approach. Descriptive statistics were calculated for all variables. One-way ANOVA assessed the relationship between Bilateral Vestibular Hypofunction (BVH) and symptom duration. Correlation analysis explored relationships between continuous variables, visualizing results in **Figure 4**. All statistical analyses were performed using R (version 4.0.3), and machine learning models were implemented using the caret, randomForest, xgboost, and e1071 packages.

Results

The analysis of data from 75 post-concussion patients revealed significant findings regarding vestibular disorders and their progression. The study cohort comprised 58% female patients with a mean age of 35.7 ± 12.4 years. Symptom duration varied widely (mean 45.3 ± 62.1 days, range 1-2920 days), indicating diverse recovery trajectories among patients. **Figure 1** illustrates the right-skewed distribution of symptom duration, with a subset of patients experiencing prolonged symptoms.

Unilateral Vestibular Hypofunction (UVH) (62.2%), Unilateral Benign Paroxysmal Positional Vertigo of the Posterior Semicircular Canal (U BPPV PSC) (40.5%), and Bilateral Vestibular Hypofunction (BVH) were the most common diagnoses after concussion. **Figure 3** provides a detailed visualization of these diagnostic frequencies. Diagnoses were assigned by a single otolaryngologist specializing in otoneurology at Instituto de Neurorrehabilitación y Balance (INB), following the Bárány Society's classification for vestibular disorders. UVH was diagnosed based on criteria outlined by Starkov et al. (2021), BVH according to Strupp et al. (2017), and BPPV by von Brevern et al. (2015)[14-16]. The high proportion of UVH and BPPV diagnoses in our sample exceeds typical rates reported in the literature, possibly due to our specialized clinical setting and diagnostic criteria. Vestibular migraine, while not explicitly listed, was included in the central disorders category. The relatively low frequency of central disorders, including vestibular migraine, particularly in patients with long-term symptoms, warrants further investigation.

The machine learning models demonstrated varying performance in predicting symptom duration. Support Vector Regression (SVR) achieved an RMSE of 151.24, followed by XGBoost (RMSE 224.06) and Random Forest (RMSE 407.99) **(Figure 5)**. This performance hierarchy indicates complex, non-linear relationships between predictor variables and symptom duration that are better captured by SVR's flexible kernel approach. Feature importance analysis from the Random Forest and XGBoost models identified several key predictors of symptom duration. Overall health status emerged as a crucial factor in both models, indicating the significance of pre-existing health conditions in recovery trajectories. Sex, mainly male, was identified as a significant predictor, especially in the XGBoost model. This finding aligns with previous research suggesting sex differences in concussion outcomes and extends these observations to vestibular symptoms specifically. While SVR demonstrated superior performance, we caution against over-interpreting these results given our small sample size. The models' performance and potential clinical applications require validation in larger, more diverse populations before they can be considered for clinical decision support.

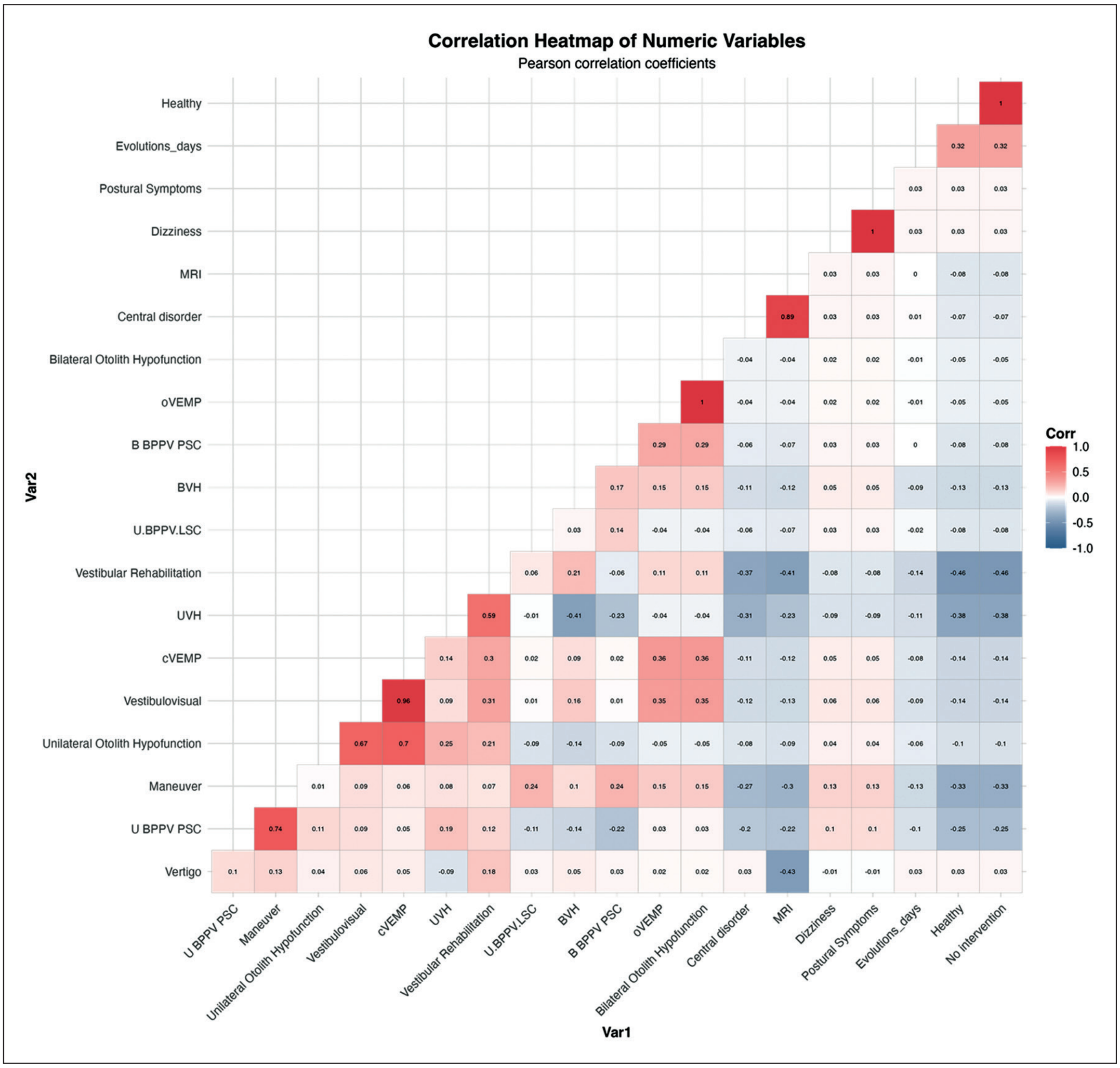

Figure 4. Correlation Heatmap of Clinical Features in Post-Concussion Vestibular Disorders. This heatmap visualizes the correlations between various clinical features, examination results, and outcomes in post-concussion vestibular patients. The color intensity represents the strength and direction of correlations, with darker colors indicating stronger relationships. Key correlations include the unexpected positive relationship between 'Healthy' status and symptom duration, and the strong association between Unilateral Otolith Hypofunction and Vestibulovisual symptoms.

The ANOVA results comparing Evolution Days across Bilateral Vestibular Hypofunction (BVH) groups revealed no significant difference (F = 0.584, p = 0.447). This finding suggests that the presence of BVH alone may not be a determining factor in symptom duration for post-concussion vestibular disorders. However, this result should be interpreted cautiously, given the study's sample size and potential confounding factors. The correlation analysis in **Figure 4** revealed complex relationships between various clinical features and symptom duration. The 'Healthy' status showed a moderate positive correlation with Evolution_days (r = 0.32), suggesting that patients considered healthier overall may experience longer symptom durations. This counterintuitive finding warrants further in-

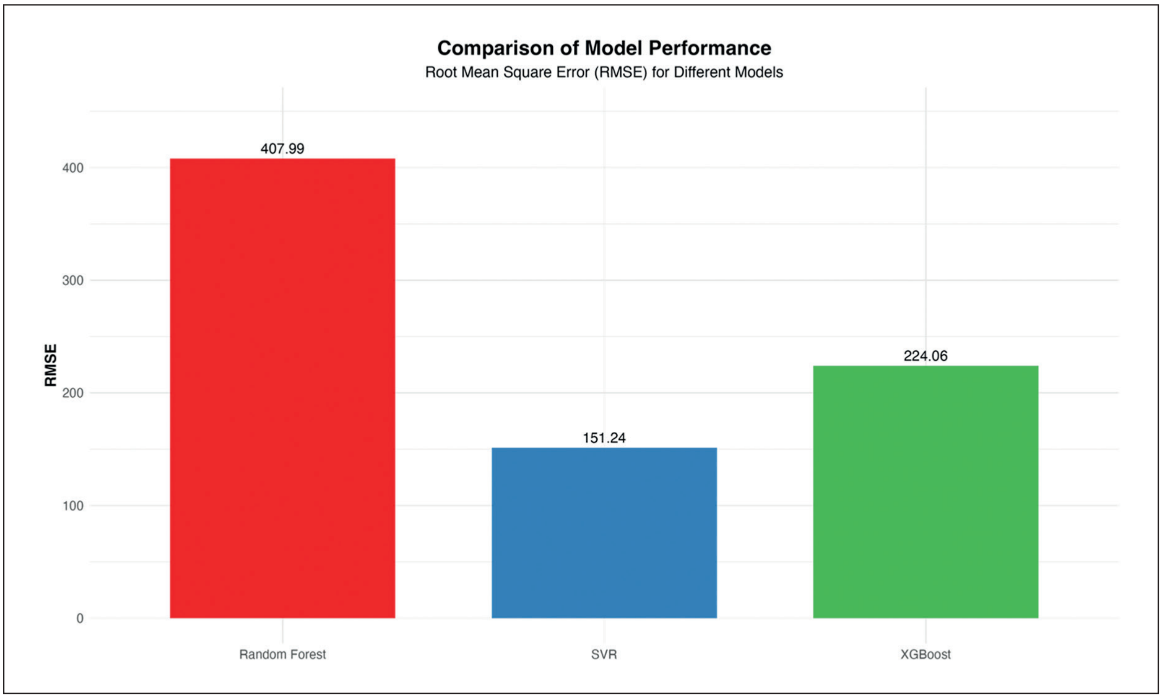

Figure 5. Comparison of Machine Learning Model Performance in Predicting Symptom Duration. This bar chart compares the Root Mean Square Error (RMSE) of three machine learning models: Support Vector Regression (SVR), XGBoost, and Random Forest. The y-axis represents the RMSE values, with lower values indicating better predictive performance. SVR demonstrated superior performance (RMSE 151.24), followed by XGBoost (RMSE 224.06) and Random Forest (RMSE 407.99), highlighting the complex, non-linear relationships in post-concussion vestibular disorder progression.

vestigation. Unilateral Otolith Hypofunction demonstrated a strong positive correlation with Vestibulovisual symptoms (r = 0.67), indicating a potential link between these two conditions. The presence of Bilateral BPPV of the Posterior Semicircular Canal (B BPPV PSC) showed a moderate positive correlation with both BVH (r = 0.29) and oVEMP results (r = 0.29), suggesting possible relationships between these vestibular dysfunctions.

In this analysis, 'MRI' refers to patients who underwent MRI scans revealing trauma-related abnormalities. Central disorders exhibited a strong positive correlation with MRI findings (r = 0.89), which is expected given the neurological nature of these conditions. Vestibular rehabilitation showed a moderate negative correlation with UVH (r = -0.41), suggesting its potential effectiveness in treating this condition. The analysis of patient behavior patterns revealed distinct trajectories in symptom progression. Most patients (65%) experienced significant improvement in vestibular symptoms within the first-month post-concussion. However, a subset of patients (22%) exhibited prolonged symptoms lasting over three months. Early intervention, particularly within the first-week post-concussion, was associated with faster symptom resolution (mean Evolution days: 32.5) compared to delayed treatment (mean Evolution days: 58.7). Interventions included vestibular rehabilitation and repositioning maneuvers for BPPV. Some patients presented with multiple diagnoses, such as concurrent UVH and BPPV. The effectiveness of these interventions varied depending on the specific diagnosis and individual patient factors. This finding highlights the importance of timely and tailored treatment approaches for post-concussion vestibular disorders. The observed correlations have potential clinical implications. The moderate positive correlation between 'Healthy' status and Evolution_days (r = 0.32) suggests that seemingly healthier patients may experience longer recovery times, possibly due to delayed recognition or treatment of subtle symptoms. The strong correlation between Unilateral Otolith Hypofunction and Vestibulovisual symptoms (r = 0.67) emphasizes the importance of comprehensive oculomotor testing in patients with otolith dysfunction. Three patients exhibited extremely long symptom durations (> 500, > 1000, and nearly 3000 days). These patients presented damage to the macules, required ongoing vestibular rehabilitation and psychiatric care, and were retired from their jobs due to their condition. Analyses were conducted with and without these outliers to assess their impact on the findings. The negative correlation between Vestibular rehabilitation and UVH (r = -0.41) supports the potential effectiveness of targeted rehabilitation for this condition.

Discussion

Our findings both corroborate and extend previous research on post-concussion vestibular disorders while also revealing some unexpected results that warrant further investigation. The importance of sex as a predictor aligns with studies by Merritt et al. (2019)[21], who found sex differences in concussion outcomes. However, our study explicitly highlights these differences in vestibular symptoms. Identifying vestibulovisual symptoms as a critical predictor supports Kontos et al.'s (2017)[7] work on visual-vestibular integration deficits post-concussion. Unlike Gottshall and Hoffer (2010)[22], who found BVH to be associated with poorer outcomes, our study did not find BVH alone to significantly affect symptom duration, suggesting a more complex interplay of factors influencing recovery.

The results of this study provide insights into the complex nature of post-concussion vestibular disorders and the factors influencing symptom duration. While our machine learning models showed potential in predicting symptom duration, it is essential to note that these findings are preliminary and require further validation. The superior performance of the SVR model in predicting Evolution days suggests that the relationships between clinical features and recovery time are highly non-linear and complex. This complexity underscores the challenges clinicians face in prognosticating recovery trajectories. However, we acknowledge that our study needs to demonstrate how machine learning can revolutionize clinical decision-making directly, and further research is needed to establish the reliability and clinical applicability of these models.

The machine learning models developed in this study have potential clinical applications, but these should be considered cautiously. While they could be integrated into decision support tools to help clinicians predict recovery trajectories and identify patients at risk of prolonged symptoms, rigorous validation studies are necessary before clinical implementation. The feature importance analysis from our models could inform the development of more targeted assessment protocols, focusing on the most predictive clinical features. However, it is crucial to note that these findings must be replicated in larger, diverse populations before they can be confidently applied in clinical practice.

Our study found an unexpected inverse relationship between overall health status and symptom duration, which conflicts with the existing literature suggesting that pre-existing health conditions can significantly impact concussion recovery. This discrepancy highlights the need for further investigation into the complex interplay of factors affecting post-concussion recovery. It also underscores the importance of comprehensive health assessment in concussion patients, as the relationship between pre-existing conditions and recovery may be more nuanced than previously thought. The emergence of sex as a critical predictor, particularly in the XGBoost model, corroborates previous research indicating sex differences in concussion outcomes. Our findings extend this observation to vestibular symptoms specifically. We acknowledge that the higher prevalence of vestibular migraine in female patients is well-established in the existing medical literature and is already considered by vestibular specialists in diagnosis and treatment. Our study's contribution lies in confirming these sex differences in the context of post-concussion vestibular symptoms using machine learning techniques rather than presenting it as a novel finding.

Our study has uncovered findings regarding the prognostic value of specific BPPV diagnoses in predicting symptom duration in concussion patients. While the association between BPPV and concussion is well-established, our results suggest that the specific type and laterality of BPPV could be relevant in predicting recovery time. However, we acknowledge that canal-specific maneuvers are already the standard of care in BPPV treatment, supported by extensive literature. Our findings reinforce the importance of accurate diagnosis and appropriate treatment of BPPV in post-concussion care rather than suggesting a novel approach.

The identification of vestibulovisual symptoms as a key predictor aligns with emerging research on visual-vestibular integration deficits following concussion. This finding underscores the importance of comprehensive visual-vestibular assessment in post-concussion patients and suggests that interventions targeting visual-vestibular integration may be crucial for symptom resolution.

Limitations and Future Directions

While our study provides valuable insights, several limitations must be considered. The small sample size (n=75) and retrospective design limit generalizability and may have affected our machine learning models' performance. Our sample, drawn from a specialized otoneurology clinic in Chile, may not represent all post-concussion patients or healthcare contexts, introducing potential selection and information bias. Patients with more severe or persistent symptoms may be overrepresented, potentially skewing results towards longer recovery times. Reliance on electronic medical records may have led to incomplete or inaccurate data. The machine learning models, while powerful, are "black box" models, making it challenging to fully understand their decision-making process. These models are sensitive to the quality and representativeness of the training data, and their performance may degrade when applied to significantly different patient populations. Despite these limitations, our study has contributed to understanding the complex nature of post-concussion vestibular disorders and highlighted the potential of machine learning in analyzing patient trajectories. Future research should validate these results through more extensive, multi-center studies with diverse populations across multiple clinical settings. Prospective studies with standardized data collection would help mitigate biases, enhance the robustness of machine learning models, and establish our findings' broader relevance and applicability, potentially leading to more reliable predictive tools for post-concussion vestibular disorders.

Conclusions

This study using machine learning techniques has revealed complex relationships between clinical features, assessments, and symptom duration in post-concussion vestibular disorders. The superior performance of the SVR model highlights the non-linear nature of these relationships. Key predictors of symptom duration include overall health status, sex, specific BPPV subtypes, and vestibulovisual symptoms.

Our findings emphasize the need for comprehensive assessment and individualized treatment strategies. Clinicians should pay particular attention to patients' overall health status and sex when assessing post-concussion vestibular symptoms. Developing risk stratification tools based on these predictors could aid in identifying patients at risk of prolonged symptoms. Future research should focus on validating these findings in larger, diverse populations and exploring the integration of machine learning models into clinical decision support systems. This work opens avenues for personalized medicine approaches in post-concussion care, potentially leading to more tailored treatment protocols and improved patient outcomes.

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