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Artificial intelligence in vestibular disorder diagnosis

Amine Ben Slama[1], Hanene Sahli[2], Yessine Amri[3,4], Salam Labidi[1]
[1]Research Laboratory of Biophysics and Medical Technologies, LR13ES07, Higher Institute of Medical Technologies of Tunis (ISTMT), University of Tunis EL Manar, Tunis, Tunisia
[2]SIME Laboratory, LR13ES03, National Higher Engineering School of Tunis (ENSIT), University of Tunis, Tunis, Tunisia
[3]Biochemistry Laboratory, Bechir Hamza Children's Hospital, Tunis, Tunisia
[4]Department of Educational Sciences, Higher Institute of Applied Studies in Humanity Le Kef, University of Jendouba, Kef, Tunisia

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ABSTRACT

Vertigo is a prevalent symptom of vestibular disorders, with ocular nystagmus analysis serving as a key indicator for distinguishing between peripheral and central vestibular conditions. Videonystagmography (VNG) provides objective and reliable measurements, making it a valuable tool for clinical assessments. However, the complexity and variability of vestibular diseases pose challenges for conventional VNG methods, such as caloric, kinetic, and saccadic tests, in accurately identifying vertigo subtypes. Traditional diagnostic approaches often fail to fully utilize nystagmus characteristics in correlating with specific vestibular disorders, limiting their effectiveness. Recent advancements in artificial intelligence (AI), particularly deep learning and machine learning (ML), offer promising solutions for improving vertigo diagnosis. These technologies facilitate automated, rapid, and precise analysis by extracting relevant clinical features and classifying vestibular disorders with higher accuracy. ML-based models enhance diagnostic reliability, reducing human bias and subjectivity in assessment. This study reviews the latest research on feature extraction and ML applications in vertigo diagnosis, emphasizing their potential to revolutionize clinical decision-making. It aims to provide a comprehensive understanding of AI-driven approaches and their role in advancing vertigo analysis, paving the way for more effective diagnostic methodologies in the future.

Corresponding Author:

Yessine Amri
Biochemistry Laboratory, Bechir Hamza Children's Hospital
Bab Saadoun Square, 1007, Tunis, Tunisia
Email: amri.yessine@yahoo.com

1. INTRODUCTION

Lots of persons in over the word are pretentious by vertigo because of the variety of peripheral vestibular disorders (VD) and the problem to report indications associated to the oculomotor scheme. The medical explanations of the shared complaints lead to discriminate dissimilar VD. Appropriate analysis and judgment opportunities have been enhanced recently, making vertigo a considerable uncomplicated difficulty to settle. Diverse indications of severe unilateral vestibulopathy are used in vestibular dysfunction diagnosis based on varied videonystagmography (VNG) tests: head shaking test, caloric test, spontaneous torsional nystagmus and removal of central disorders by the use of neurological assessment [1], [2].

Typically, vertigo analysis is completed through ear, nose and throat (ENT) doctors based on visual examination of eye movement employing insufficient clinical parameters obtained from the vestibulo-ocular response (VOR). This assignment is moderately inappropriate. Still, the examination of this disease is error prone and time consuming. The effectiveness of this assessment is extremely reliant on the expert attention and assistances [3]. The automated analysis of VD does not substitute the physicians; but, it can assistin acquiring reliable and rapid detection. Computerized systems used to judge and classify VD pathologies have the potential to make a substantial contribution to healthcare. The chief objective of these classification procedures is to recognize the diverse categories of vestibular pathologies and to control the actual measures from temporal pupil movement parameters that assist experts in vertigo analysis [4]. In medical interpretation, the VD diseases can be split into two groups: canalolithiasis disorder and sensory dysfunction. Correlative clinical assessments should be completed using the VNG technique in order to assure the effectiveness of the processing, where the topographical analysis of vestibular system are exposed with a high-quality accuracy.

Dizziness symptom is assessed by the use of VNG technique by providing clinical clarification and well examining central nervous system (CNS) [5]. Vertigo integrated different vestibular disease types [5], [6] that reduce the eye and head movement's functionality. This is caused disequilibrium via a unilateral reflectivity of the vestibule. The obtained measurement can be affected of the vestibular ocular channel that mostly incomes evaluating an anomalous eye movement related to diverse VNG stimulation. The reflectivity measure yields completely dissimilar meaning employing both of caloric and kinetic tests. This later uses practically a stimulus on the pair of semicircular canals (SCC). This kinetic test enables a calculation of the greatest of slow phase velocity (SPV) from the nystagmus attends the chair stop. It is the simply test able to generate an ideal connection between stimulation and VOR test [6], [7]. Caloric test is wholly competent to discover and appraise one vestibule at once. The calculation of the reflectivity between the right and left ears is achieved by measuring the cumulative collection of nystagmus slow velocities following inner ear irrigation with cold and warm water for a duration of 20 seconds.While, caloric test will permits monitoring of unilateral reflectivity variations on some patient because we can take up that thermic transfer state via the middle ear is the similar from an assessment to another. Consequently, the head-shaking test (HST) is reliable and more apt than kinetic and caloric stimulations that supply an examination of both central and peripheral vestibular purpose at elevated frequency [8]-[10]. In practice, the VOR response is frequently typified by a nystagmus waveform restraining a slow phase followed by a fast phase which does not stand for the real test of the vestibular system. Hence, the rhythmic eye movements can serve as a valuable indicator in describing peripheral as of central vestibular disorders (CVD) such as, vestibular neuritis (VN), Ménière's disease (MD) and vestibular migraine (VM), and benign paroxysmal positional vertigo (BPPV) compared to healthy cases (HL).

The vestibular-ocular reflex does not accurately give details about the underlying cause of sensory disorder, and could not determine the slow velocities of pupil movement [11] focused on eye movement response following the simulation. The nystagmus variation in pathological cases can be similar to that of HL when considering the reserved amplitude of ocular movement. Still, the nystagmus evaluation totally needs more relevant information for improved vestibular dysfunction recognition. In effect, the consistency of the VD diagnosis is associated to the VOR measurement related to the cervical proprioception, the vestibular system and the vision [12]. The ideal scenario is that the eye rotation axis aligns with the head rotation axis, and the VOR gain is close to 1, reflects normal case. Clinically, where as the gain is inferior to 0.8 is considered abnormal. A gain cutoff of 0.7 ideally differenciate between peripheral and central vestibular pathologies. To evaluate the true vestibular response and assess peripheral vestibular function, it is necessary to identify the fast and slow phases through VNG recordings. The chief complexity in the vertigo appraisal through VNG examination is that there is no crucial indicative reference for comparing it with the alternative instance. It is essential to verify that nystagmus has been properly assessed by the examination of the eye movement waveform trace for nystagmus measurement and component separation. Several saccades are revealed by an ocular instability using a VNG recording. The saccadic phases occur in diverse forms presented to Dell'Osso and Jacobs [13]. A stimulation of the SCC is carried on based on different VNG tests such as head impulse test, kinetic test, and caloric test. The VOR is not a reliable indicator for determining the underlying cause of a sensory disorder, nor can it accurately measure the slow velocities of nystagmus [12]. Compared to frequency measure, the nystagmus SPV is moderately informative. An ocular motor response with the frequency is used for the VOR presence or absence detection. For improving the diagnostic process of the vestibular disease [14], a statistical model is developed for predicting vestibular diagnoses, prior to clinical assessment. Peripheral vestibular disease (PVD) refers to dysfunction in the vestibular region, specifically involving the structure of the eighth cranial nerve and can also occur in the labyrinth of the inner ear. It is characterized by sensitive peripheral disorder that caused impulsive vertigo [15], VN assigns the vestibular labyrinth, forming the superior division of the vestibular nerve [16]. Patients affected by VN exhibit different types of nystagmuswhich beat away from the lesion side. This dysfunction can indicate either VN or bilateral vestibular response loss.

The positive HST has elevated specificity for neuritis disease based on VNG responses. It is regularly complicated for experts and its nonappearance may be symbol of a stroke. Regarding to a deficit on eye movement fixation, a torsional-horizontal nystagmuscould be revealed through the Dix–Hallpike test [17]. It should be noted that the interpretation of such dysfunction can sometimes be misleading, as the nystagmus observed in benign positional dizziness can be mistakenly attributed. The latency and low nystagmus response absence may not be recognized by the non-clinician. Added truthful diagnosis of dizziness would help in the decision which patients necessitate treatment. Yet, MD implies the higher centers of cortical function, the cerebellum, midbrain, and the vestibular nuclear complex. The sensory input from a somatosensory, visual and vestibular systems are involved by the CVD structure. Migraine syndrome can be an indication of CVD [18]. In some medical way, experts cannot recognize the vestibular dysfunction associated to migraine pathology. PVD decreases the right neural information for nystagmus, postural control and spatial orientation. Ménière's pathology reveals to be the endolymphatic regulatory dysfunction sign. Furthermore, dizziness symptom is characteristically presented by hearing task, ear pressure, and change in tinnitus. Evidently, there is an important relation between the history of fluctuating hearing loss and vertigo symptom in patients. According to the seriousness of symptoms, medical and surgical processing's are available. Around 10-30% of cases affected by VM expand episodic dizziness lasting minutes to hours [19].

Certainly, clinicians use visual examination of eye rotation using inadequate clinical features derived from the VOR, which is prone to errors. The effectiveness of this assessment relies on both the attentiveness and proficiency of clinicians. While computerized assessment of VD does not replace ENT doctors, it can assist them in achieving reliable and rapid diagnoses. The primary objective of automated methods is to identify different types of VD and extract accurate parameters from temporal eye movement measurements [20]. In medical observations, it is essential to conduct supplementary clinical testing using the technique to ensure the efficacy of the treatment.

This paper focuses on the use of artificial intelligence for assessing vestibular dysfunction. The structure of the paper is as follows: section 2 examines various datasets and parameters employed for training different models in in the differential diagnosis of vertigo and vestibular disorders and section 3 presents a conclusion of this study.

2. SURVEY METHOD OF VERTIGO ANALYSIS

2.1. Data analysis for machine learning in a vertigo case

The VNG technique includes so many experiments for kinetic functions, exploitation, oculomotor saccadic, tracking, and caloric irrigation for both vestibular ocular responses VOR ear canals. For the initial analysis of reflectivity, preponderance, and hypovalence, we proceed with a kinetic, saccadic, and caloric test in order to identify the causes of vertigo symptoms, which could be explained by an imbalance of inner ear damage (peripheral disorder) or problems in parts of the brain (central disorder). As stated in Table 1, we present in the current study the different parameters utilized during VD assessment via VNG tests.

Table 1. Clinical VNG extracted features

VNG tests	Caloric test	Kinetic test	Saccadic test	Head shaking test
Measures	Ref DP H	G RDP AP	V P	SPV
Significance	Reflectivity	Gain	Velocity	Slow phase velocity
	Directional preponderance	Relative directional preponderance	Precision	
	Hypovalence	Absolute preponderance		

Classification methods are commonly employed to handle overlapping database partitions, particularly in the context of classifying clinical parameters [20]. It is widely recognized that the accuracy of the classification process heavily relies on the effectiveness of the preprocessing stage which is performed to select the original features obtained from VNG tests. The utilization of these features can improve the implementation integrity and minimize the computational time during the classification process. Indeed, classification of medical datasets is a tough undertaking due to the large diversity in their feature distribution [21].

Nowadays, several prospective classification approaches are currently described in the literature in order to avoid the overlap and provide relevant features for datasets classification [22]. Numerous studies have demonstrated that vertigo can be categorized into multiple vestibular dysfunction categories [23], [24]. These studies have also highlighted that an identical nystagmus waveform can lead to false-positive VOR indications, which can result in inaccurate parameters for characterizing vestibular diseases. Understanding the corresponding nystagmus patterns and their relationship to different disease levels is often beneficial.

Different types of nystagmus expressions can provide insights into the severity or specific characteristics of certain VD. The VNG technique is used to treatperipheral vestibular dysfunction and to highlight vertigo symptom characterized by ocular nystagmus (Figure 1). In the current study, vestibular diseases are classified based on their temporal and frequency features obtained from various VNG tests into three groups (i.e., VN, MD, and VM).

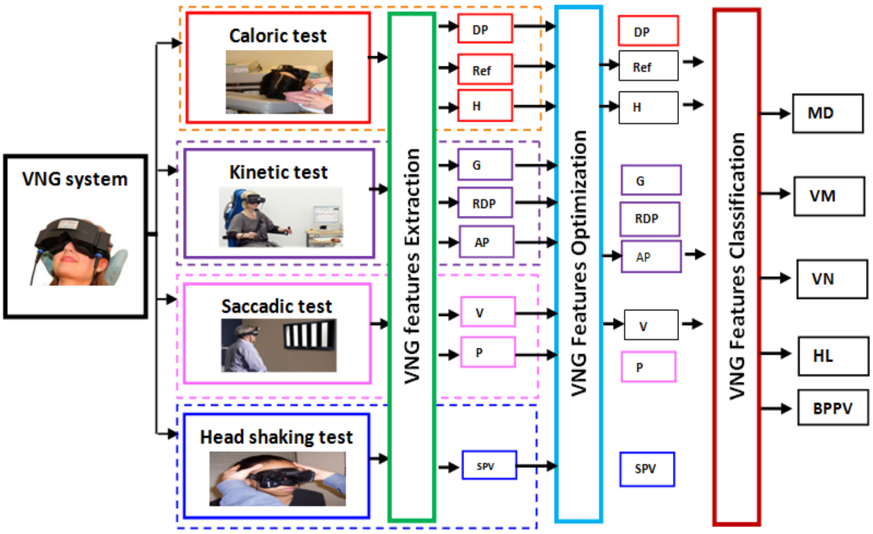

Figure 1. Manual assessment of VD using VNG technique

Certainly, the analysis of vertigo through VNG methods has faced numerous challenges. Certainly, there is no conclusive and entirely dependable assessment that ensures an effective analysis. Additionally, for the computation of eye movements and separation of components, it is essential to confirm that nystagmus has been accurately identified by inspecting the trace and establishing the two phases.

Based on nystagmus waveform, many researches [25], [26] have been presented to aberrant eye movement employing the information of the SPV like an effective support for a perfect diagnosis evaluation. In patients with peripheral VD, the VOR measurement [27] is an interesting diagnostic factor which is usually utilised to understand the canal lesion origin and the vestibular system functionalities. Furthermore, gathering VOR information in kinetic test is a complex process which necessities a variety of technical procedures. In the study of Wadehn *et al.* [28], multiple methods are presented using electro-oculography (EOG) in order to remove blinks noise as well as to extract the two ocular nystagmus components. On the other hand, Mantokoudis *et al.* [29] described an attractive method used to remove fast phases from nystagmus signal using Kalman filter algorithm. Indeed, the use of the Kalman filter and SVM was developed by the authors in [30], where the algorithm detect and track pupil region. The eye detection is accomplished by simultaneously use the bright/dark pupil effect under active IR brilliance and the eye appearance characteristics under ambient lighting via the SVM technique. Otherwise, all of these studies are aimed to improve the eye tracking procedure in VNG sequences without addressing the problem of nystagmus feature extraction and its effect on the VD diagnostic process.

Indeed, caloric and kinetic tests cannot only analyse one vertigo-related symptoms, i.e., the eye movements [31] and the VOR response which requires a complex evaluation. Consequently, the identification of the optimal parameters from common VNG tests necessitates the selection of the most relevant features using the Fisher discriminate analysis in order to raise the effectiveness during the classification process. Indeed, the main contribution of the present study is the proposal of an automatic method for VD identification in VNG data that has never been defined previously. The suggested method involves both features reduction and VNG parameters classification. Concerning the feature reduction, an approach based on Fisher's linear discriminant (FLD) analysis is firstly used.

Afterward, a sparse representation classifier is employed to distinguish among different VD from normal cases. Indeed, in a prior investigation conducted by Slama *et al.* [32], the categorization network was used to identify and assess VN solely using clinical characteristics acquired from optokinetic and caloric tests. However, the classification procedure in the research presented in [33] has been significantly enhanced due to the implementation of the suggested pupil tracking technique and its precision in providing crucial temporal and frequency characteristics from caloric and kinetic tests.

The significance of this study [33] is emphasized by the application of integrated nystagmus features obtained from four VNG tests (head shaking, kinetic, saccadic, and caloric) to differentiate between various VD conditions and healthy individuals. The complete VD evaluation methodology is employed on a large number of participants using a database comprising 90 patients affected by three distinct VD conditions and 30 normal subjects. Furthermore, the efficacy of the proposed method is showcased through a comparison with the multilayer neural network (MNN) classifier. A statistical measure outcome from four experiments was arbitrarily chosen for each classification technique.In contrast to the quantification provided by experts, the suggested methodology demonstrated the ability to identify three cases of VD with an average accuracy of 92% in the entire dataset [33].

2.2. Machine learning approaches used in the differential diagnosis of vertigo

For BPPV, VM or MD and VN disease, continue vertigo charges can last seconds to minutes, more than hours, or for days to a few weeks; respectively. Dissimilar peripheral and central vestibular diseases are regularly accompanied by dilemma for instance basilar and VM. During riding and boat trips, rotatory vertigo and postural imbalance are linked to VN and bilateral vestibulopathyrespectively.

Vertigo short hits may happen in Ischaemia, VM and MD for adults. The data was collected processed by CCD digital camera [26] and focused on VNG medical technique. In VNG sequences, the frame size and rate are 1024×720 and 30 fps; respectively. Via the proposed analysis method, the accumulated data is studied, trained, and evidently assessed. Kinetic, saccadic, caloric irrigation, pursuit and oculomotor exploitation are tests of the proposed system. Exhibiting the clinical interest of VNG examinations, saccadic, caloric and kinetic tests are advanced for key measurements. Considering the advance in disequilibrium measurements that might be constructive, the vertigo assessment has very quickly improved. Making a decision of tangible therapy, surgical and medical procedure will happen constantly focused on the simultaneous evaluation of complete crucial measurements. Given the earlier understanding, it is commonly favored to response analysis of SPV in cephalic movement in place of frequency [34]. If the velocity measurement presents a very huge error resulting, the experts income by measuring the vertigo intensity. Therefore, the examination interpretation will present a greater difficulty as there is no straightforward and direct link between the nystagmus frequency and SPV.

This section explores the contemporary research on ML methodologies applied in the categorization of vertigo. A feature-based approach in lieu of relying on the traditional technology-based technique is followed to structure the literature. This is owing to the insufficient amount of information in the literature pertaining to the application of ML techniques. For specific targeted issues, researchers employed a variety of diverse algorithms. Mapping the applications and grouping them together focused on data types, employed features, or both, facilitates the process. Categorizing the literature based on algorithm usage can be challenging due to the abundance of available algorithms, leading to a higher number of subsections with a relatively smaller number of articles focusing on each specific algorithm.

The utilization of the feature-based method in this study facilitated a comprehensive understanding of the ongoing advancements in distinct subdomains. It also revealed the algorithms currently employed for specific features, thus providing valuable insights and paving the way for future research directions. In this work, our exploration focuses on the literature sources that have utilized ML algorithms specifically on the ONE and VNG datasets. Joutsijoki *et al.* [35] employed the half-against-half (HAH) algorithm in combination with support vector machines (SVM), k-Nearest Neighbors (KNN), and naïve Bayes (NB) techniques. The results showed that the HAH-SVM approach exhibited comparable the classification accuracy to the One-vs-One (OVO) SVM method. In the study conducted by Varpa *et al.* [36], the authors employed a genetic algorithm (Gen)-based approach for attribute weighting in the ONE database. They compared this method to combined OVA weighted KNN and weighted KNN techniques. The classification results showed that the attribute weighting using the genetic algorithm improved the disease classification results for all the tested methods. Shilaskar *et al.* [37] addressed the issue of class imbalance in the dataset by employing under-sampling of the majority class and synthetic oversampling of the minority class. They used a modified particle swarm optimization (PSO) algorithm for feature selection and SVM to enhance the accuracy of the results. In their study, Iltanen *et al.* [38] utilized a decision support (DS) system along with KNN techniques to classify seven different vertiginous cathegories via the ONE database. The attribute-weighted 5-nearest neighbor method demonstrated high accuracy in achieving efficient results.

Table 2 presents the results for the state of the art studies applied on the clinical ONE and VNG dataset, showing the mean accuracy for different classes noted as follows: VN: vestibular neuritis, VS: vestibular schwannoma, MD: Ménière’s disease, VM: vestibular migraine, BPPV: benign paroxysmal positional vertigo, SD: sudden deafness, TV: traumatic vertigo, VNE: vestibular neuritis, ANE: acoustic neuroma, and BRV: benign recurrent vertigo.

Table 2. Performance of classification results of ML algorithms on ONE and VNG database

Literature		Joutsijoki *et al.* [35]	Varpa *et al.* [36]	Shilaskar *et al.* [37]	Iltanen *et al.* [38]	Mouelhi *et al.* [33]
Year		2013	2014	2017	2017	2020
Data	VN					✓
	MD					✓
	NL					✓
	VM					✓
	VN					
	BPPV	✓	✓	✓	✓	
	ANE	✓	✓	✓	✓	
	SD	✓	✓	✓	✓	
	VNE	✓	✓	✓	✓	
	MD	✓	✓	✓	✓	
	TV	✓	✓	✓	✓	
	BRV	✓	✓		✓	
Sample size		1030	951	815	1030	120
Class number		7	7	6	7	4
Method		HAH-SVM, KNN	Gen- KNN	PSO-SVM	DSS-KNN	FLD-SRC
AC (%)		65	74.15	92	79.7	92.24

2.3. Machine learning applications in nystagmus and vestibulo-ocular reflex tests

During the step of pupil segmentation, different techniques are applied using Geodesic active contour (GAC) algorithm [26], and Hough transform approach which use the VNG sequence by maximizing the ratio of the interclass variance and minimizing the intra-class variance to the total variance. The aim is to separate the foreground pixels (the eye-pupil) from the background. The morphological operators yield intriguing outcomes within the realm of VNG processing. During this stage, the spurious pixels induced by the infrared light are eliminated by means of the opening and closing operations. The objective of this phase is to identify the boundary of the pupil in the processed frame and ascertain its central position. Taking into account the aforementioned procedures, an elliptical curve derived from pixel projection is employed to estimate the region of the pupil. The two smaller and larger axes of the ellipse correspond, respectively, to the segmented horizontal and vertical pupil, while the center of the ellipse can be obtained from the peak position with (x, y) coordinates.In each frame of the VNG sequence, the pupil region is identified utilizing the GAC approach [26]. Indeed, the GAC method for pupil tracking was previously proposed in the study of Slama *et al.* [26] and was solely implemented for VNG sequences pertaining to VN disease. Moreover, in several studies, the evaluation of nystagmus intensity is predominantly calculated based on the frequency and amplitude of SPV and the saccadic phase (fast phase) of nystagmus, which are commonly utilized as standard measurements in both the time and frequency domains. The extraction of temporal and frequency features using GAC and active contours methodologies is a vital undertaking in the vestibular assessment. The rotational angle of pupil movement is computed after the pupil segmentation phase in nystagmuscharacterization. In the published literature, two approaches are used for this purpose: cross correlation method and template matching technique [26].

The authors compute the rotation angle of eye movement using just the pupil location in different subsequent VNG frames, based on methods developed by Iijima *et al.* [39] for nystagmusidentification without the manual selection of iris. The rotation angle deviation of nystagmus is computed as (1):

$$\theta_n = \frac{cos^{-1}(x_n)}{\sqrt{{x_n}^2+{y_n}^2}} - \frac{cos^{-1}(x_1)}{\sqrt{{x_1}^2+{y_1}^2}} \tag{1}$$

where θ_n presents the rotation angle of pupil coordinates (x_n,y_n).

In alternative investigations, to quantify the amplitude of spontaneous nystagmus and assess the actual VOR associated with peripheral vestibular function arising from bilateral or unilateral vestibular dysfunction, the identification of slow and fast phases from nystagmographic recordings becomes indispensable as key components in a robustly designed diagnostic procedure for VD. The primary challenge in evaluating VNG investigations for vertigo lies in the absence of crucial benchmarking scenarios to compare them with diverse diagnoses.

The parameters derived from the slow and fast phases, including the frequency, amplitude, and duration of nystagmus, can serve as a valuable aid in ensuring a seamless assessment of therapy effectiveness. To precisely ascertain the temporal and frequency-related nystagmus characteristics, we have employed the linear interpolation technique to extract the slow and fast phases identified by independently determining the boundaries of the fast phases. The primary concept underlying this technique is to estimate the rotation angle θ at a specific moment t by utilizing a straight line that connects two instants t_j and t_{j+1} close to t,

$$\theta(t) = a_0 + a_1 t \quad (2)$$

Here, the initial point of the fast phase is regarded as the last moment tj of the preceding slow phase, while the second point t_{j+1} corresponds to the first moment of the subsequent slow component a_0 and a_1 present the coefficients of a the linear function.
The stated coefficients can be computed using the system of (3), (4):

$$\theta_j = \theta(t_j) = a_0 + a_1\ t_j \quad (3)$$

$$\theta_{j+1} = \theta(t_{j+1}) = a_0 + a_1\ t_{j+1} \quad (4)$$

Solving the system of equations for the coefficients a_0 and a_0, the function y(x) takes the form on the interval [tj,tj+1]:

$$\theta(t) = \theta_j + \frac{t-t_j}{t_{j+1}-t_j}(\theta_{j+1} - \theta_j) \quad (5)$$

The assessment of VNG tests is based in reality on the individual variability of the VOR response (slow phase of nystagmus). Indeed, in certain cases [40], the SPV measurement might provide wrong evaluation that requires further characteristics for an accurate clinical VD prognostic. Thus, the common signs of this VD do not provide significant information from simple nystagmus movement's study. Moreover, only slow phase is required to determine the real VOR response.

Nevertheless, in some cases [41], the SPV measurement produces erroneous assessment which needs additional characteristics for an appropriate clinical VD prognosis. In particular, the dysfunctional side of the inner ear disrupts the common vestibular function of the intact side. In this situation, the slow component of nystagmus has to compensate the reduced response of the dysfunctional side shown a fast phase in kinetic test compared to the regular response of normal case in kinetic and caloric tests.

2.4. Classification of videonystagmography features for vestibular disorders diagnosis

In the study proposed by Smith *et al.* [42], the authors place partial emphasis on enhancing the analysis of VD. In this context, the preprocessing stage plays an essential role in ensuring accurate evaluation of the prevalent vestibular diseases, closely addressing the challenges associated with the VNG technique. Additionally, we would like to remind that there is really some technical works to recognize the cause of vestibular abnormalities. Only a few studies [14], [26] addressed the analysis of VD based on nystagmus analysis.

The nystagmus signals extracted from the vestibular system are challenging to analyze clinical parameters; also, ENT doctors take a lot of situations into account before understanding the clinical implication of all VNG measurements and deciding the diagnosis report. In the work of Slama *et al.* [26], a personalized process is planned in order to facilitate the vestibular dysfunction diagnostic on reduced features that illustrate the indication of VD disorders. Indeed, the performance of a clinical VNG can be shown in terms of standardization in the medical analysis process or the ability of the parameters from different tests to discriminate affected patients by peripheral diseases and normal cases.

In this framework published by Slama *et al.* [26], authors proposed a Fisher criterion technique to select the most pertinent VNG features for VD analysis that can enhance the classification results of VD. Also, a combination of extracted features using PCA or FLD process from VNG dataset is applied to train the neural networks for the VD classification. To increase classification results, all previous works [43], [44] have concentrated their analysis all VNG features extracted from the clinical VNG tests.

The superiority of neural networks technique [26] is highlighted by the use of different temporal and frequency parameters by some adapted VNG processing approaches, and the application of the most discriminative parameters for the VD classification was defined in the study of Slama *et al.* [26]. The method proposed in [44] provides effective features able to classify a VNG datasets with an accuracy rate of 97.06% compared to others classifiers using PCA-MNN [26], and CNN [43] technique. It was the highest recognition accuracy when compared with other considered methods, revealed in Table 3. Furthermore, the work presented in [44] arranges numerous contributions within the framework of developing an expert diagnosis. The comparative studies demonstrate that the suggested methodologies are resilient and effective in designing a computerized diagnostic system for vestibular dysfunctions.

The proposed methodologies are employed for the identification of the specific VD category and provide a clinical assessment for ENT experts, thus highlighting cases that require additional attention and minimizing the rate of confusing cases. Based on the existing accuracies reported in the literature, it is intriguing to consider the parameters obtained through various feature extraction techniques (such as time-frequency analysis of clinical features derived from conventional VNG tests and VNG processing) as relevant metrics that can be employed for evaluating vestibular dysfunction.

Table 3. A comparison results between different previous VNG classification methods

Literature	Features	Classifier	# of classes	Accuracy (%)
[26]	PCA features	PCA-MNN	2: VN+, VN-	95.5
[43]	Time domain based on nystagmus feature	CNN	2: VN, Men, NL	96.36
[44]	Time-frequency domain features derived from EMD energy entropy of the first eight IMFs	DBN-DNN	3: Men, Mg, NL	97.06

Undoubtedly, the suggested method can reduce the dependence on clinical information in the training database of the classification process. Consequently, this significant deep learning technique is employed with utmost focus to preserve essential information, enhance computational efficiency, and ensure the efficacy of the classification method. In this regard, ENT doctors can acquire supplementary clinical information regarding VD when analyzing the significance of VNG measures, thereby offering a secondary opinion for ambiguous cases that require further attention.

2.5. Overview of vertigo and vestibular disorders diagnosis

In this context, the classification process is employed to differentiate between classes of peripheral and CVD diseases. In recent studies [43], no established computerized approach has been identified that can consistently be employed to accurately identify types of vestibular dysfunction without utilizing all the parameters extracted from VNG tests. This is in contrast to previous research [36], this study is regarded as exceptional in its approach to vestibular dysfunction classification and the utilization of crucial VNG features to develop an automated system for VD analysis.

In the work of Kim *et al.* [45], authors applied ML algorithms on a simple clinical information, and can achieve analysis for vertigo disorders. Certain optimized algorithms, integrated within embedded systems and employing trained machine learning (ML) methods, can aid non-expert physicians in the preliminary assessment of vertigo and disease classification, as highlighted in the study [26]. Zhang *et al.* [46] proposed a deep learning architecture that can directly record VNG eye movement and classify different nystagmus forms into subtypes of BPPV disease.

Also, in the work of Filippopulos *et al.* [47], authors propose the use of AI-based classification methods to enhance diagnostic accuracy rate and outcomes confusing cases with vertigo conditions. Current existing studies that have utilized deep learning and ML algorithms have underlined the limited availability of clinical information of VNG datasets [36]. In addition, some small sizes of clinical datasets and missing data values in clinical VNG recording system can decrease the achievement of deep learning and machine learning algorithms.

The use of a large clinical datasets to train the machine learning or deep learning models can give high classification results. However, various inappropriate features that do not contribute as a descriptive factor of a disease type among high-dimensional data which need preprocess that can reduce the feature-set dimension. In this context, some studies have focused on feature extraction and transformation methods to decrease the feature-set dimension, achieving preventing overfitting [48], [49] and increased classification accuracy. Also, The machine learning and deep lerning techniques in existing literature [43], [44] suggest an automated system for VD disease prediction by interpreting different complex clinical VNG dataset, using preprocess feature selection and determination.

3. CONCLUSION

Vertigo diagnosis is principally focused on diverse VNG parameters via well-known VNG tests (kinetic, caloric, and saccadic). This syndrome necessitates appraisal and judgment from neurological experts due to its ponderous and time consuming treatment. This paper summarizes the employ of current artificial intelligence methods in the disparity diagnosis of sensitive vertigo. Regardless of the extended history of using machine learning and deep learning approaches for neuro-otological treatments, a finer diagnostic hold up system has not yet emerged. Publicly accessible datasets with varied vertigo presentations with the new analysis results are feasible to incite future researchers to start much-required work in this field.

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Amine Ben Slama	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓		✓	
Hanene Sahli		✓		✓		✓		✓	✓	✓	✓	✓		
Yessine Amri	✓	✓	✓	✓			✓		✓	✓	✓		✓	✓
Salam Labidi	✓		✓	✓			✓			✓	✓		✓	✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflict of interest.

ETHICAL APPROVAL

This study was carried out under the principles of the Declaration of Helsinki developed by the World Medical Association and approved by the Human Ethics committee of Bechir Hamza Children's Hospital of Tunis.

DATA AVAILABILITY

For data evaluation please contact Dr. Ben Slama Amine at: amine.benslama@istmt.utm.tn.

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BIOGRAPHIES OF AUTHORS

Amine Ben Slama (Ph.D.) received a doctorate degree in Biophysics and medical imaging and member of research group in Research Laboratory of Biophysics and medical technologies at ISTMT - University of Tunis El Manar. His research interests include image and signal processing, application of artificial intelligence for brain tumors and vestibular disorders classification. He can be contacted at email: amine.benslama@istmt.utm.tn.

Hanene Sahli (Ph.D.) received her doctorate in Science and Technology with a specialization in Electrical Engineering from the National Higher School of Engineers of Tunis (ENSIT), University of Tunis. Since 2020, she has been an Associate Professor of Signal and Image Processing at the University of Kairouan. She is also a researcher at the Signal, Image, and Energy Mastery (SIME) Laboratory. Her research focuses on machine learning and deep learning applications in biomedical image analysis and security, particularly in intrusion detection systems. Her work contributes to advancing artificial intelligence-driven methodologies for signal and image interpretation. She has published several papers in international journals. She can be contacted at email: sahli.hanenne@gmail.com.

Dr. Yessine Amri Dr. (Ph.D.) received his Bachelor's degree in Medical Biotechnology and a Master's in Genetics and Biodiversity from the Higher Institute of Biotechnology of Monastir, Tunisia, followed by a Ph.D. in Pharmaceutical Sciences from the Faculty of Pharmacy of Monastir. He is a member of the Biochemistry and Molecular Biology Laboratory (LR00SP03) at Bechir Hamza Children's Hospital. Currently, he serves as an Assistant Professor at the Higher Institute of Applied Studies in Humanities, Le Kef. His research interests focus on machine learning applications, genetic disorders, molecular biology, and bioinformatics. He can be contacted at email: amri.yessine@yahoo.com.

Salam Labidi since her Ph.D., she started developing her research career by focusing on radiation protection. She is currently a Professor of Biophysics at Higher Institute of Medical Technology of Tunis, University of Tunis El Manar, Tunisia. Since 2012, she started getting interested in medical imaging. She directs the research team "Radiation Protection and Biological Image" at Laboratory of Biophysics and Medical Technology, Tunis, Tunisia. She has several published papers in international journals. She is the President of Doctoral Thesis Committee (biophysics, medical physics, and medical imaging). She can be contacted at email: salam.labidi@istmt.utm.tn.