Development of a Hand-Arm Vibration Syndrome (HAVS) Detection Tool for Construction Workers

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Abstract –

Hand-Arm Vibration Syndrome (HAVS) results from prolonged exposure to hand-held vibrating tools, such as jackhammers, drills, and grinders. Construction workers frequently use these tools for extended periods and are therefore prone to developing HAVS over time. HAVS can affect the vascular, neurological, and musculoskeletal systems of workers, leading to both short-term and long-term disability. Despite its severity, HAVS is often under-reported due to a lack of awareness and delayed detection. Existing methods for detecting HAVS primarily focus on assessing the vibration levels of hand-held equipment rather than the condition of the exposed workers. This study proposes a machine learning tool to assess the hand and arm conditions of construction workers exposed to vibrating equipment. The tool is capable of analyzing hand drawings to detect hand tremors, an early symptom of HAVS. This innovative approach offers a potential solution for the regular monitoring of construction workers' health, enabling early detection and management of HAVS symptoms.

Keywords – HAVS; Machine Learning, Construction Workers Health; Hand Tremor

1 Introduction

The construction industry is one of the most hazardous industries around the world in terms of both fatal and non-fatal injuries. Global reports estimate approximately 60,000 fatal injuries take place within the construction industry around the world [1]. In the United States alone, approximately 200,000 non-fatal injuries and illnesses take place every year and the number go significantly higher when it comes to global injuries in the construction industry [2].

Since construction is a labor-intensive industry, the health and safety of construction workers become significantly important. A major factor affecting the health and safety of these workers is the physical demanding and hazardous nature of their work environment, particularly their reliance on heavy, hand-held machineries such as jackhammers, drills, and grinders to complete tasks [3]. These tools are heavily used in the industry for works such as demolition, drilling, cutting, etc. These tools generate intense vibrations due to their high speed and powerful mechanical operations which are then transmitted to the hands and arms of the workers.

Depending on the equipment type and specifications, the level of vibration can range from moderate to extreme. Studies show that approximately 1.2 million workers in the United States are potentially exposed to hand-arm vibration syndrome risks and among them 500,000 are construction workers [4]. To make things worse, often these tools generate more vibrations than the manufacturers declare. The Hand-Arm Vibration Database [5] on the Physical Agents Portal website collected a total of 4,913 field vibration measurements from 2,897 pieces of equipment and compared their field values with the manufacturer-declared values. This database shows that in the majority of cases, the field values are significantly higher than the declared ones [5]. Exposure to these tools with higher vibration rates and longer duration can cause significant damage to the construction workers' health. Over time, these vibrations can damage soft tissues, nerves, and blood vessels, particularly when workers are exposed for extended periods without adequate breaks or protective measures [6-8]. Additionally, weather conditions, particularly cold and wet environments, significantly worsen the risk of HAVS for construction workers [9]. Cold weather constricts blood vessels, increasing susceptibility to Vibration White Finger (VWF), while wet conditions reduce grip efficiency, amplifying strain on hands and arms [10]. These factors, combined with prolonged outdoor exposure, heighten workers' vulnerability to developing HAVS over time.

Despite these eminent dangers, HAVS is often under-reported or undetected in the construction industry due to the intermittent nature of symptoms. Studies suggest that workers wait more than 3 years after symptom onset before seeking any treatment related to HAVS and approximately 9 years before receiving a proper assessment [11]. Workers also tend not to report the early symptoms due to lack of awareness. Hence, it is necessary to assess HAVS among the workers regularly, especially those involved in hand-held heavy machinery usage.

This paper proposes a machine learning tool that can assess the workers' hand tremor condition by analyzing their hand drawing. The tool is trained on Parkinson's disease patients' dataset and can analyze the condition of the construction workers' tremor condition and characterize them as HAVS.

2 Hand-Arm Vibration Syndrome (HAVS)

Hand-Arm Vibration Syndrome (HAVS) is a progressive condition caused by continuous exposure to vibration from tools and machinery [12, 13]. It is characterized by symptoms such as tremor, tingling, numbness, reduced grip strength, and loss of fine motor skills, and can affect the vascular, neurological, and musculoskeletal systems [6, 14]. At advanced stages, HAVS can lead to chronic pain and permanent loss of hand function, severely impairing a worker's ability to perform tasks and maintain their livelihood [15, 16]. Vibration exposure can also exacerbate other musculoskeletal disorders, creating compound health risks. Beyond its physical toll, HAVS has economic consequences for both workers and employers, including increased healthcare costs, compensation claims, and decreased productivity [17, 18].

HAVS has been reported across different industries such as manufacturing, mining, forestry, automotive etc. where workers operate vibration-intensive equipment. The prevalence of HAVS among workers regularly exposed to vibration averages 50% and increases over time if corrective measures are not implemented [19]. Studies have shown a high prevalence of HAVS in specific occupational groups, such as foundry workers, where up to 47% of exposed workers may have advanced stages of the syndrome [12].

While HAVS is a concern in different industries, it is particularly prevalent and severe in the construction industry [20]. Workers in the construction industry are regularly exposed to vibrating tools such jackhammers, concrete saws, angle grinders, pneumatic drills etc. The construction environment exacerbates HAVS risks due to prolonged tool usage, lack of awareness, and inconsistent implementation of safety measures [21, 22]. Studies suggest that up to 63% of the construction workers may be affected by HAVS to some extent [23]. In Europe, it is estimated that one in four workers are exposed to either hand-arm vibration or whole-body vibration [24]. In the United States, an estimated 1.45 million workers use powered tools that generate hand-arm vibration, with the prevalence of HAVS ranging from 6% to 100%, with an average of about 50% [25].

3 Point of Departure and Research Objectives

In order to prevent the severe health consequences of HAVS, early detection and intervention is crucial. HAVS detection involves evaluating workers' physical symptoms, functional impairments, and their exposure history [26-29]. There are clinical and technological approaches to detect HAVS among workers. For example, the Vibrotactile test evaluates the level of sensitivity of the mechanoreceptors in the hand [30], while the Thermal Aesthesiometry test assesses the sensitivity of thermal receptors in the hand to changes in temperature [31]. There are other tests such as the Purdue Pegboard test [32], Grip Force Measurement test [33], Cold Provocation test [34] etc. that assess the patients' level of sensitivity and fine motor skills in hands. Although these assessment methods are clinically effective, these strategies can be applied only when the workers self-report some of the symptoms of HAVS. However, in many cases it has been observed that workers often overlook the early symptoms and do not self-report the symptoms [7, 11, 35, 36]. By the time they report their symptoms, it is often too late.

In recent times, researchers have come up with some strategies to detect potential HAVS among construction workers by measuring the level of vibration in hand-held equipment. For example, studies demonstrated the technical feasibility of using the integrated microphone and accelerometer from commercial smartwatches in identifying the level of vibration the hand-held tools generate [25, 37, 38]. However, these methods only assess the hand-held tools' level of vibration rather than the condition of the workers' hands and arms due to the exposure to these vibrations. Additionally, these tools heavily rely on data collected through sensors in smart watches. It is often observed that these sensors collect a lot of noise from surroundings due to the dynamic nature of construction activities.

To address these issues and detect HAVS symptoms among construction workers, this research proposes a machine learning tool that can analyze the hand-drawing of construction workers and assess the condition of their HAVS in real time and continuously over a period. The tool is easy to use and does not require any wearable sensors. The tool can analyze the hand-drawing of workers, especially those exposed to vibrating tools for a longer duration and detect any vibrating syndrome such as tremor in their hands.

4 Methodology

4.1 Development of the HAVS Assessment Tool

Our methodology for developing the HAVS assessment tool is rooted in the motivation of detecting various diseases, such as Parkinson's disease, from hand drawings. Despite originating from distinct causes and affecting different parts of the nervous system, HAVS and Parkinson's disease share similarities, particularly in their effects on motor function and the nervous system. One of the common symptoms for both diseases is hand tremors. Although the causes for hand tremors differ, their effects are indistinguishable. Consequently, given the apparent scarcity of datasets dedicated to HAVS detection, our proposed machine learning model is trained using datasets primarily created for detecting Parkinson's disease [39]. The dataset primarily consists of drawings of wave and spiral shapes, both from healthy individuals and patients affected with Parkinson's. Spiral drawings, in particular, are highly effective in recognizing hand tremors of both resting and active types associated with Parkinson's. This is because tremors cause drawn lines to become relatively uneven and wavy compared to smooth spirals drawn by healthy individuals. As HAVS primarily involves hand arm vibration, it can also be associated with tremoring hands, making this approach particularly useful.

The Hand Arm Vibration Syndrome (HAVS) detection framework proposed in this study can be divided into three distinct modules which will be described in the following subsections sequentially. Figure 1 describes the structure of the proposed system.

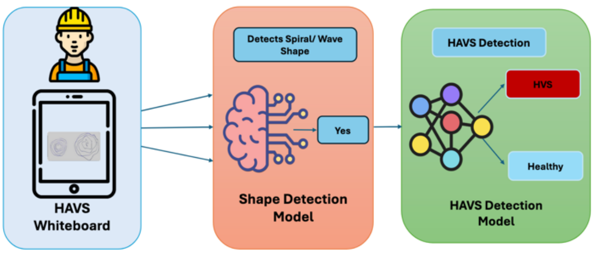


Figure 1. Proposed HAVS System Architecture with three modules.

4.2 HAVS-Whiteboard

To facilitate the collection of drawings from construction workers, a standardized online virtual drawing board is essential. While numerous virtual drawing tools are available, a dedicated tool is necessary to create a compact system that is entirely independent of any third-party application. This system must ensure the privacy and security of construction workers' sensitive information from various malicious inference attacks, such as Health Attribute Inference Attack and Personality Inference Attack, as it is shown that drawing-based inference attacks allow unauthorized intruders to accurately predict the personality and health condition of the concerned individual [40]. We envision to develop the HAVS-Whiteboard as a mobile application.

The data collection process in the HAVS-Whiteboard system begins with initialization of an empty data structure to store all the drawing-related information. Each stroke, defined as the continuous movement of the pen from contact to lift-off, is assigned a unique identifier to ensure proper segmentation of the data. This enables the system to differentiate between individual drawing actions. A sample HAVS-Whiteboard interface is demonstrated in Figure 2.

When a user starts drawing (pen-down event), the system captures the starting position of the pen on the canvas (x, y coordinates), the pressure applied, and the precise timestamp of the interaction. This starting point is the beginning of a new stroke, and a unique stroke ID is generated. As the user continues to draw (pen-move event), the system records data points at regular intervals. Each data point includes the pen's current position, the pressure applied, the angle of the pen, and the timestamp. Additionally, the speed of the pen's movement is calculated in real time by dividing the distance between two consecutive points by the time elapsed between them.

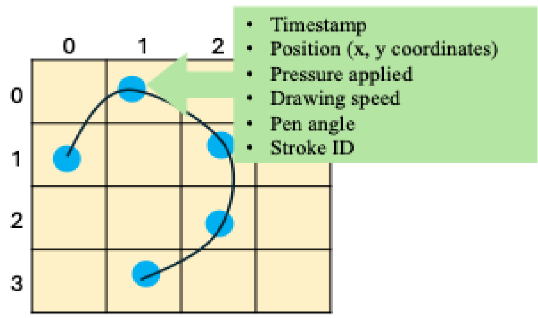


Figure 2. Data collection on HAVS-Whiteboard interface.

When the user lifts the pen (pen-up event), the stroke is finalized, and the system compiles all the captured data for that particular stroke. This process repeats for every new stroke. The collected data is securely stored and includes attributes such as timestamp, position, pressure, speed, pen angle, and the corresponding stroke ID.

In our current implementation, the HAVS-Whiteboard, a Python-based standalone application, captures the (x,y) coordinates and timestamp information. We plan to continue enhancing the application by implementing additional features, which we intend to utilize for data collection from construction workers. Our discussion of the subsequent modules of the architecture is focused on the current state of the implementation.

4.3 Disease Detection Model

Our detection model is built upon the concept of training a deep convolutional neural network model using Spiral and Wave images of the aforementioned dataset. Convolutional Neural Networks (CNNs) unlike the traditional machine learning models like SVM, Random Forest etc does not require manual feature extraction and remarkably effective for identifying hierarchical features like textures, edges etc from images while at the same time showing increased resiliency towards noise and distortions. But the problem arises from the fact that, training a deep CNN model is a tough nut to crack due to the requirement of high quantity of task related quality which is pretty difficult to ensure for each task. This seemingly unsolvable dilemma can be solved by a process which is commonly known as Transfer Learning. Transfer Learning involves finetuning a pretrained model, which has been trained on a large dataset, for a particular task. In this work, we used a pretrained deep CNN model called MobileNetV3Large which has been trained on ImageNet dataset and finetuned for our HAVS detection task. Figure 3 below illustrates the architecture of the HAVS detection model.

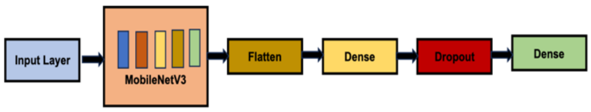


Fig 3. Block Diagram of Detection Model

4.4 Shape Recognition Model

As our proposed detection model is solely trained on Spiral and Wave images, while deploying this very HAVS detection system in real-life scenarios, there remains always a distinct possibility of users generating drawing other than Spirals or Waves. In these types of cases, how robust our detection system may be, it is bound to face failure. So, for uninterrupted operation of the detection model, it must be ensured that only related Spiral and Wave images are forwarded to that system discarding any other shapes. That's where the concept of using Shape Recognition Model comes from. It will primarily work as a filter whose very purpose will be to protect the detection model from unwanted shape images. In this work, we used the same DCNN model called MobileNetLargeV3 that we used for detection task using Transfer Learning. The difference lies in the fact that we finetuned this MobileNetLargeV3 with a dataset to detect whether the input image shape is Spiral or Wave.

MobileNetV3 is an open-source lightweight deep CNN model which has been primarily designed for producing efficient inference results in resource constrained devices such as Smartphones, Embedded Systems and IoT devices. It uses depth wise convolution which separates simpler convolutions into two distinct categories - Depthwise Convolution and Pointwise convolution which reduces the computational cost while still maintaining significant accuracy. Our particular version of MobileNet which is MobileNetV3 uses a squeeze-and-excitation module which helps module to focus on most informative feature channels while ignoring the less relevant ones thus improving its performance over the baseline one. Figure 4 presents the block diagram of the MobileNetV3 architecture, highlighting its key components such as depthwise and pointwise convolutions, bottleneck blocks, and the squeeze-and-excitation module, which collectively enable efficient and accurate feature extraction. As we want to focus on deploying this model in future on edge devices for real time use by the users, this model with its lightweight architecture, less susceptibility to noise and requirement of less computational power becomes a natural choice for the proposed HAVS detection system.

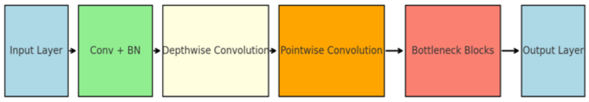


Figure 4: Block Diagram of MobileNet Architecture

5 Experimental Setup and Result Analysis

The entire experiment was implemented in Python using Pytorch framework for training and testing the model and NVIDIA's A100 GPU. Different performance metrices starting from Accuracy, Confusion Matrix, Precision, Recall and ROC-AUC curve have been used for evaluating the performances proposed Shape Recognition and HAVS detection model.

Confusion matrix is a tabular summary of model's predictions compared to actual outcomes which is widely used for evaluating model's performance. Table 1 describes the confusion matrix for both HAVS detection and Shape Recognition Model.

From Table 1, it is clearly visible that our modified finetuned MobileNetV3Large based Shape Detection model performs exceptionally well for both Healthy and Parkinson/HAVS categories where it is nearly perfect while correctly predicting Spiral and Wave Shapes. This Shape detection model works as a gateway to the detection mechanisms, it's highly accurate performance suggests its reliability as a filtering tool. In the case of HAVS model, it is evident that it's ability to differentiate between Healthy and Parkinson/HAVS drawing is significantly better for Spirals compared to Wave drawings where it produces some False Positives.

Table 1. Category Specific Confusion Metrices

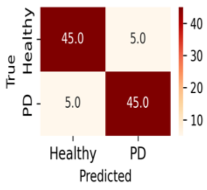
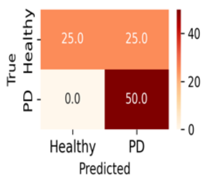
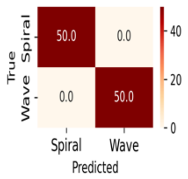
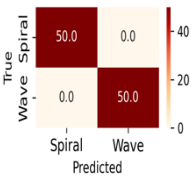
HAVS Detection Model		
	Spiral	Wave
Shape Detection Model		
	Healthy	Parkinson/HAVS

Table 2 demonstrates the category specific results of other metrices such as Accuracy, Precision, Recall, F-1 Score which are usually generated from confusion matrix for both models.

Table 2. Category Specific Results of Performance Metrices.

		Accuracy	Precision	Recall	F-1
HAVS Detection Model	**S**	0.83	0.82	0.87	0.84
	W	0.93	0.93	0.93	0.93
Shape Detection Model	**H**	1.00	1.00	1.00	1.00
	P	1.00	1.00	1.00	1.00

Here S=Spiral, W=Wave, H=Healthy and P=Parkinson/HAVS.

From the above table, it can be observed that the shape recognition model works perfectly for both categories, HAVS model performs well especially for Wave drawings but there are areas of improvement to be done.

6 Discussion

The development of a HAVS assessment tool leveraging machine learning and existing Parkinson's datasets represents an innovative approach to address the challenge of limited HAVS-specific data. By using Spiral and Wave drawings as a means to detect hand tremors, the study successfully demonstrates the potential of integrating this tool as a method of continuous monitoring of hand-tremor development among construction workers. The integration of a custom-built virtual drawing tool i.e., HAVS-Whiteboard, enhances data security and privacy, addressing critical concerns in real-world applications.

Another finding of this research is the effectiveness of transfer learning with MobileNetV3Large in achieving robust performance on both Shape Recognition and HAVS Detection tasks. The Shape Recognition model displayed near-perfect accuracy, acting as a reliable filter to ensure only relevant input reaches the detection model. However, while the HAVS Detection model performed exceptionally well on Wave drawings, its slightly reduced accuracy for Spiral drawings reveals areas requiring further refinement. This discrepancy highlights the importance of feature representation in the input data, as Spiral patterns may involve subtler tremor-induced variations compared to Wave patterns.

Additionally, the study underscores the importance of implementing a lightweight architecture for edge deployment. MobileNetV3's efficiency, low computational overhead, and resilience to noise make it a natural choice for resource-constrained environments, such as construction sites.

The inclusion of multiple performance metrics ensures a comprehensive evaluation of the proposed system. However, analyzing false positives and negatives reveals opportunities for improving the model's ability to differentiate between Healthy and HAVS-related cases, particularly in complex scenarios. Furthermore, the reliance on Parkinson's datasets introduces potential biases, necessitating the collection of HAVS-specific data to enhance generalizability and reduce overfitting to Parkinson's-like features.

7 Conclusion

The study presents the development of a machine-learning-based tool designed to detect Hand-Arm Vibration Syndrome (HAVS) among construction workers. This innovative tool utilizes drawing patterns, captured through timestamps and (x, y) coordinates of drawing, to identify potential symptoms of HAVS.

While the current proof of concept has been validated using simple spiral and wave-like drawings, future iterations of the tool will incorporate additional features to enhance accuracy. In the next phase of development, we will expand the dataset by collecting real-world drawing samples from construction workers who are exposed to hand-held heavy machinery and integrating richer data, such as pressure, speed, and pen tilt. This will enable us to fine-tune the model and improve its reliability in identifying HAVS among construction workers.

The findings highlight the potential of machine learning to revolutionize occupational health monitoring by providing a scalable, efficient, and accurate tool for early detection of HAVS symptom. The integration of such tools can significantly improve the well-being of workers, reduce the burden of health-related risks, and enhance safety outcomes in high-risk industries. With further refinements and real-world validation, this framework can serve as a foundation for broader applications in health diagnostics and safety monitoring.

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