International Journal of Industrial Ergonomics 108 (2025) 103775

Contents lists available at ScienceDirect

International Journal of Industrial Ergonomics

journal homepage: www.elsevier.com/locate/ergon

Comparative analysis of classical and ensemble models for predicting whole body vibration induced lumbar spine stress. A case study of agricultural tractor operators

Amandeep Singh[a,f,*], Naser Nawayseh[b], Philippe Doyon-Poulin[a], Stephan Milosavljevic[c], Krishna N. Dewangan[d], Yash Kumar[e], Siby Samuel[f]

[a] Department of Mathematics and Industrial Engineering, Polytechnique Montréal, 2500 Chem. de Polytechnique, Montréal, QC H3T 1J4, Canada
[b] Department of Mechanical and Nuclear Engineering, College of Engineering, University of Sharjah, 27272, Sharjah, United Arab Emirates
[c] School of Rehabilitation Science, College of Medicine, University of Saskatchewan, Saskatoon, S7N 2Z4 Saskatchewan, Canada
[d] Department of Agricultural Engineering, North Eastern Regional Institute of Science and Technology, Nirjuli, 791109, India
[e] Iowa Technology Institute, The University of Iowa, Iowa City, IA 52242, United States
[f] Department of System Design Engineering, University of Waterloo, N2L 3G1, Ontario, Canada

ARTICLE INFO

Keywords:
Whole-body vibration
Daily equivalent static compression dose
Lumbar spine stress
Classical regression
Ensemble modeling
Ensemble meta-modeling
Explainable artificial intelligence

ABSTRACT

Accurate prediction of lumbar health is necessary for developing effective ergonomic strategies for tractor operators exposed to whole-body vibration. This study aims to predict static compression dose (S_{ed}), a key measure of lumbar spine stress as per ISO 2631-5, by comparing classical regression and ensemble models. Three tractor operation parameters (average speed, average depth, and pulling force) are considered to assess S_{ed} during rotary tillage operation. The performance of two classical models (Linear and Huber regression) is compared with five ensemble models (Random Forest, Gradient Boosting, XGBoost, AdaBoost, and Bagging regressors) in predicting S_{ed}. The comparison identifies the best models in each category, with linear regression achieving a mean bootstrap R^2 of 0.91 (95 % CI: 0.87 to 0.94) and Random Forest achieving 0.93 (95 % CI: 0.90 to 0.95). To further enhance performance, meta-models are developed using two meta-learners (Random Forest and Gradient Boosting) to integrate classical and ensemble models. These models are optimized using different ensemble strategies: simple averaging, weighted averaging, stacking, and voting regressors. Among these, the stacking method proves most effective, achieving a mean bootstrap R^2 of 0.94 (95 % CI: 0.93 to 0.96). Feature importance analysis reveals that the multi-model combination of ensemble models achieves the highest predictive score (0.99) for S_{ed}. These findings demonstrate that ensemble models outperform classical models in predicting Sed, particularly when combined through stacking methods. This advancement has significant implications for improving occupational health and safety among tractor operators, potentially leading to better ergonomic tractor designs aimed at reducing lumbar spine stress.

1. Introduction

From 1971 to 2021, the number of tractors used in Indian agriculture increased from 0.168 to 9.173 million (Mehta et al., 2024). India now manufactures approximately one-third of global tractor production (Mehta et al., 2019), making it a significant player in the global agricultural machinery industry. This significant tractor usage and production growth emphasizes addressing operator health and safety issues. However, occupational health concerns faced by agricultural workers in India have historically received limited attention (Dewangan et al., 2023), despite the increased mechanization. With the high degree of tractor use, a safe and comfortable working environment for the operator becomes important to enhance productivity and operator satisfaction (Benos et al., 2020). Moreover, farmers are becoming more aware of ergonomic risks, including physical exposures and injury hazards.

One of the major ergonomic concerns associated with agricultural vehicles is the exposure of operators to high levels of whole-body vibration (WBV). WBV contributes significantly to health risks,

* Corresponding author. Department of Mathematical and Industrial Engineering, Polytechnique Montréal, Montreal, Canada.
E-mail addresses: amandeep.singh@polymtl.ca (A. Singh), nnawayseh@sharjah.ac.ae (N. Nawayseh), philippe.doyon-poulin@polymtl.ca (P. Doyon-Poulin), knd@nerist.ac.in (K.N. Dewangan), ydhabi@uiowa.edu (Y. Kumar), siby.samuel@uwaterloo.ca (S. Samuel).

https://doi.org/10.1016/j.ergon.2025.103775
Received 18 October 2024; Received in revised form 21 March 2025; Accepted 9 June 2025
Available online 20 June 2025

discomfort, and reduced productivity (Bovenzi and Betta, 1994; Milosavljevic et al., 2011; Zeng et al., 2017). Studies have consistently demonstrated that WBV is transmitted primarily through the seat to the buttocks and back, and through the floor or footrests to the feet (Mehta and Tewari, 2000; Rakheja et al., 2020). In extreme cases, vibration exposure is sufficiently severe to compromise operator balance and control (Lines et al., 1995). The four principal adverse effects of increased ride vibrations include degraded health, impaired activities, degraded comfort, and motion sickness (ISO 2631-1:1997, 2010). Prolonged exposure to vibrations, particularly near the resonance frequency of the human body, significantly contributes to vibration-induced discomfort (Griffin, 2007). Furthermore, vibration exposure contributes to fatigue, reducing productivity among tractor operators (Krajnak, 2018). Studies have also shown that vehicle operators have the risk of developing musculoskeletal disorders, particularly lower back pain (Eger et al., 2008; Killen and Eger, 2016; Tiemessen et al., 2007; Wahlström et al., 2018; Zanatta et al., 2019; Zhang et al., 2019; Zhang and Guo, 2023). Lower back disorders are more prevalent among tractor operators compared to the general population due to the greater magnitude of tractor vibration compared to on-road vehicles (Bovenzi and Betta, 1994; Singh et al., 2018b). These findings emphasize the urgent need to develop effective strategies aimed at reducing WBV exposure among tractor operators, thereby mitigating health risks and improving overall well-being and productivity.

Several studies have reported elevated WBV exposures in operators various vehicles. Marin et al. (2017) reported that the 8-h vibration dose value (VDV(8)) and 8-h static compression dose (S_{ed}) were significantly higher in mining vehicles. Based on these exposures, it was recommended to reduce vehicle operator time by 50–66 % to remain within daily exposure (A(8)) vibration tolerance limits. Langer et al. (2015) examined the effect of four-wheel drive on WBV in tractors with large square balers, showing that the four-wheel-drive mode, especially during downhill operations, increased WBV exposure, highlighting its influence on the longitudinal dynamics and vibration exposure of tractors. Chang et al. (2011) found that dump truck operators in Taiwan experienced vibration exposures exceeding ISO 2631-1 (1997) action limits. Another studies identified high vibration exposure levels during on-farm vehicle use in New Zealand and Canada (Milosavljevic et al., 2012; Zeng et al., 2017). In India, Sed during rotary soil tillage operations was evaluated and found to range between 0.38 and 0.76 MPa, indicating a moderate risk of adverse health effects (Singh et al., 2019). Forward speed and pulling force had significant effects on S_{ed}, contributing 64.43 % and 24.73 % of the variation, respectively. Similarly, Singh et al. (2022) reported that speed and water level significantly affected Sed during operations with water tankers, exceeding ISO 2631-5 limits. These findings highlight the critical need for addressing WBV exposure specifically within agricultural contexts in India.

Previous research has focused on measuring vibration exposure under various operational conditions, examining factors such as seat cushions, cab suspension, shock absorbers, tire pressure, and vehicle speed, predominantly focusing on overall ride comfort. For example, Mehta and Tewari (2010) measured WBV exposure during operations with different implements, evaluating various cushion materials for damping characteristics, finding high-density polyurethane foam most effective. Velmurugan et al. (2012) reported WBV levels exceeding ISO 2631–1:1997 upper limits during tractor semitrailer operations under varying conditions, highlighting significant health risks. Nguyen and Inaba (2011) investigated the impact of tire characteristics on vibrations transmitted to tractors, emphasizing influences from speed and tire pressure. Adams et al. (2004) demonstrated improvements in tractor ride comfort through central tire inflation systems, highlighting significant reductions in resonant frequencies and ride discomfort. Deprez et al. (2005) optimized nonlinear suspension systems in off-road vehicles using in situ measurements, effectively enhancing comfort. Singh et al. (2018a) assessed tractor ride comfort during rotary tillage operations and found WBV levels ranged from "fairly uncomfortable" to "uncomfortable" (according to ISO 2631–1:1997; see section C.2.3 – comfort reactions to vibration environments in this standard), largely driven by tractor velocity and draft force. Another study further validated the substantial WBV exposure exceeding ISO 2631-1: 1997 recommended exposure action values (Singh et al., 2023b). In addition, the frequency response at the seat pan was primarily observed within the 4–7 Hz and 8–13 Hz frequency ranges, with the vibration energy fluctuating across this low-frequency spectrum during tillage.

Despite extensive WBV research, predictive modeling of WBV-associated health risks using advanced machine learning (ML) techniques remains underexplored (Chan et al., 2022; Prakash et al., 2025; Singh et al., 2023c). Based on the literature review, several studies have successfully applied ML techniques in different vibration exposure contexts, including bus operators (Hanumegowda and Gnanasekaran, 2022), knee joint vibration signals (Zheng et al., 2021), gender differences in horizontal transmissibility (AlShabi and Nawayseh, 2022), high-impact shovel loading operations in surface mining (Ali and Frimpong, 2021), diagnosed whole-body vibration faults in aeroengines (Fei and Bai, 2013), and dumper operators in mining (Ramar et al., 2023). However, ML applications for tractor operators remain significantly underexplored, with existing studies focusing on psychophysiological workload (Lu et al., 2020; Pei et al., 2019), workload assessment (Hota et al., 2023), driving performance (Zhao et al., 2024) and ride comfort (Singh et al., 2023c; Zhang et al., 2024). Critically, limited attention has been given to health risk prediction, especially S_{ed} (an important health risk parameters to assess the lumbar spine stress from WBV exposure). This limitation is particularly critical as tractor operators experience complex WBV exposures influenced by multiple nonlinear factors such as variations in soil properties, implement attachment/operating conditions, tractor speed fluctuations, driver anthropometry etc., which traditional statistical methods struggle to capture and model effectively. Advanced ML techniques can capture these nonlinear interactions, making them highly suitable for developing robust prediction models (Chakraborty et al., 2024; Zhou et al., 2024).

Given the diverse range of ML algorithms available, it is essential to identify those that can leverage the strengths of multiple approaches to capture complex nonlinear relationships and enhance predictive accuracy. While existing ML models show promise, there is still significant potential to explore more advanced computational approaches, particularly ensemble methods (Abimannan et al., 2023; Campagner et al., 2023; Mohammed and Kora, 2023; Yang et al., 2023). Ensemble models are particularly effective in capturing nonlinear relationships mitigating overfitting, and balancing bias and variance (Ganaie et al., 2022). While most ML-based studies utilize single (individual) models to test their predictive strength; an individual model's performance may not always be sufficient for practical implementation, particularly when considering dynamic operational conditions typical of agricultural environments. In such cases, multi-model ensemble approaches can combine multiple algorithms and often outperform any single model (Jiang et al., 2024; Manjunatha and Tsiotras, 2023). Although deep learning models have gained popularity, they often face challenges (e.g., overfitting, computational complexity), particularly with complex WBV datasets (Jiang et al., 2024). Conversely, ensemble models typically require less data to train, incur lower computational demands (Cao et al., 2020), and are less prone to overfitting (Ganaie et al., 2022). Nonetheless, even advanced ensemble approaches must address model transparency and interpretability, which are essential for adoption in real-world settings, especially in ergonomics and safety policies. Explainable AI (XAI) techniques provide information into the influence of operational features and the models used in multimodal approach for S_{ed} predictions, enabling practitioners, policymakers, and designers to make informed decisions such as tailoring interventions, optimizing tractor suspension designs, implementing ergonomic seating solutions, and refining operational guidelines for different soil and terrain conditions.

The present study aims to develop an accurate and robust predictive model for assessing health risks associated with WBV exposure among tractor operators during rotary soil tillage operation. Specifically, this research evaluates health risk according to ISO 2631-5 by computing the S_{ed} parameter. The predictive performance of two classical models—Linear and Huber Regression—is compared with five ensemble models—Random Forest, Gradient Boosting, XGBoost (Extreme Gradient Boosting), AdaBoost (Adaptive Boosting), and Bagging Regressors—in predicting S_{ed}. The bootstrap method evaluates model stability and confidence intervals (Bhutamapuram and Sadam, 2022), aiming to identify the optimal model within each category. Subsequently, meta-models are developed separately from the classical and ensemble models using two meta-learner methods (Random Forest and Gradient Boosting) to improve prediction performance. These models are then combined using four ensemble strategies: simple averaging, weighted averaging, stacking with linear regression, and voting regressors (Ganaie et al., 2022). Moreover, an XAI-based feature importance analysis (Kumar and Taylor, 2024) is conducted to ensure transparency and interpretability in understanding the importance of operational parameters (tractor speed, pulling force and tool depth). Additionally, predictive models (used to develop a multimodal) are tested to determine their impact on S_{ed}. We hypothesize that ensemble-driven multi-model approaches can demonstrate better performance in predicting S_{ed} under WBV exposures while maintaining interpretability through XAI procedure.

2. Methodology

This section outlines the detailed research methodology for developing prediction models for predicting S_{ed}. It includes the details about participants, tractor ride features, target variable, experimentation, feature engineering, classical and ensemble models, meta-model development, ensemble-based meta-model development with different methods (simple averaging, weighted averaging, stacking with linear regression, and voting regressors), hyper tuning and optimization and model interpretability approach. Fig. 1 illustrates the methodological framework for the development of Ensemble Meta-Models.

2.1. Participants

Tractor operators were recruited from Punjab Agricultural University (Ludhiana, India) based on the following criteria: (i) a minimum of two years of tractor-driving experience, (ii) absence of any self-reported musculoskeletal disorders, and (iii) no known hypersensitivity to vibration. This selection aimed to ensure participants were sufficiently experienced and capable of managing field-based tractor operations under actual working conditions. Interested operators were initially briefed on the study's objectives and procedures. Those volunteered underwent a screening process to confirm they met the inclusion criteria. The final set of five participants was chosen because of limited field availability. Unlike on-road studies, soil tillage experiments require fresh field patches to maintain consistent soil conditions (such as moisture content, soil strength, weed intensity etc.) across each experiment run. Once a portion of the field has been tilled, its soil properties changes, which would introduce variability and potentially confound the vibration exposures. To ensure consistent exposure levels and reliable data, each participant performed three repeated experiments without reusing the same tilled area. In this case, including more than five participants would have required reusing the tilled area of the field, potentially compromising data reliability. The study's primary focus is on data-driven prediction modeling rather than broad epidemiological generalization. However, the selected participants reflect typical anthropometric characteristics of young, healthy tractor operators in the region, providing a reasonable foundation for training predictive models on vibration exposure. While the findings are applicable to similar working populations, further validation would be required for generalizing the developed models to other demographic groups.

Prior to data collection, the study protocol was reviewed and approved by the Institutional Ethics Committee of the GNDEC, Ludhiana (India). Permission for experimental resources (such as field, tractor, machinery and manpower) was granted by Punjab Agricultural University, Ludhiana (India) [VC-4545]. Written informed consent was obtained from each participant in accordance with the Declaration of Helsinki and institutional guidelines.

The five participating tractor operators were male, aged between 21 and 25 years (mean 22.8 years). Their heights ranged from 1.70 to 1.81

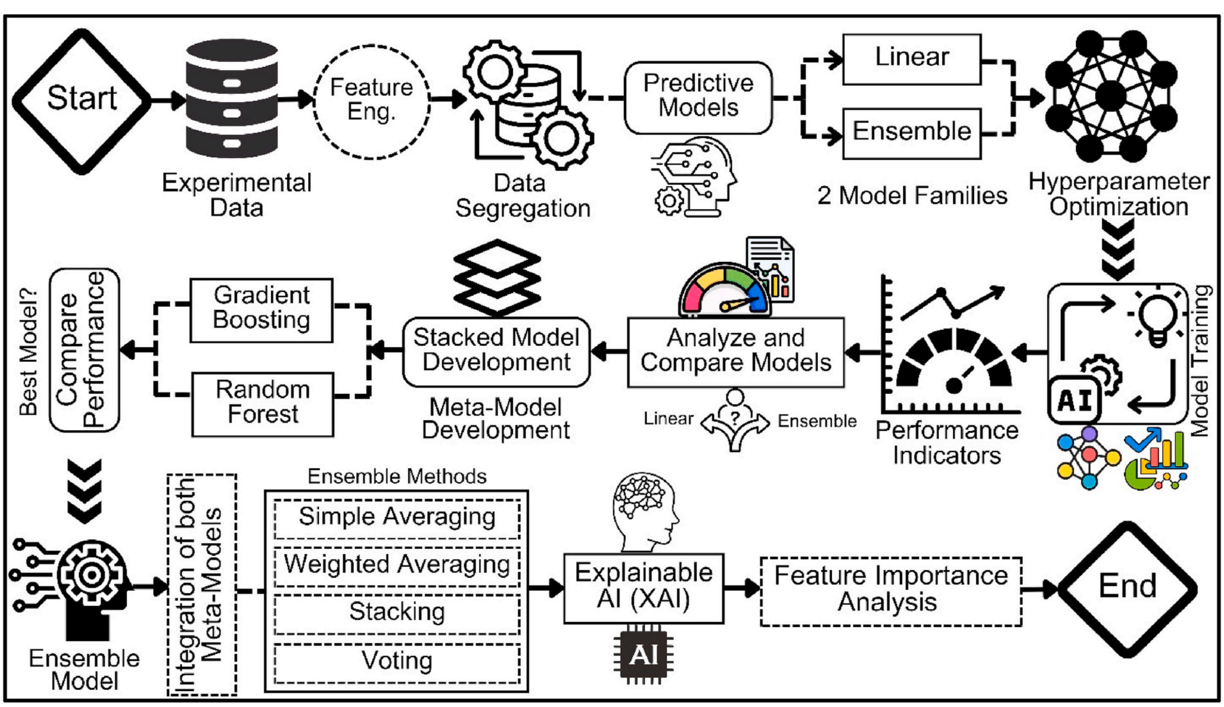

Fig. 1. Methodological process of the ensemble meta-model development.

m (mean 1.75 m), and their weights ranged from 65 to 79 kg (mean 71 kg), resulting in a mean body mass index (BMI) of 23.32 kg/m^2. This BMI range falls within normal limits and may reduce inter-participant variability in certain anthropometric factors. This range also represents a typical BMI distribution for young tractor operators in the study region. Therefore, these participants can be considered reasonably representative of young, healthy tractor operators in this agricultural setting. Including participants with a normal BMI helped reduce anthropometric biases in assessing vibration-induced lumbar stress and ensured a more reliable dataset for prediction model development.

2.2. Machinery, instrumentation and experimental design

The study was conducted in a wheat-harvested field. Prior to the experiment, soil samples were collected from four random locations and analyzed for texture according to ISO 14688–1:2002 standards. The soil was categorized as sandy clay loam, with a composition of 66.25 % sand, 9.27 % silt, and 27 % clay. The soil moisture content was measured in accordance with ISO 17892–1:2014, ranged from 48.61 % to 55.43 %. Soil strength was measured using a digital cone penetrometer, with values of approximately 12 kPa, 22 kPa, and 29 kPa at depths of 0–0.06 m, 0.05–0.11 m, and 0.10–0.16 m, respectively. A 2-wheel drive 41 kW tractor (Model: FT 65 EPI Farmtrac, Make: Escort Kubota Limited, India) was used for the experiments and was fitted with a standard manufacturer-installed seat. This particular tractor was selected because it is commonly used in the region. It represents typical power and operational characteristics relevant to local farming practices. A rotary tiller of dimensions 1.35 × 2.50 × 0.94 m and weighing 455 kg was attached to the tractor. The working width of the rotary tiller was 2.13 m and it was fitted with 48 C-shaped blades distributed across 8 flanges. The tiller could tile soil up to a depth of 0.15 m. This tiller design is popular among the farmers of the region due to its efficient soil-cutting capabilities and lower energy consumption compared to alternative rotary tillers (L or J shaped blades).

This study utilized Internet of Things (IoT) technology for remote vibration measurement (Singh et al., 2023b). The system employed an ESP8266 microcontroller to transmit vibration data to the cloud via Wi-Fi, enabling real-time remote monitoring. The SV106 vibration analyzer was integrated into the IoT system by connecting it to the ESP8266 through an RJ45 Ethernet port. The microcontroller was programmed to read data from the analyzers through this interface, converting the data into a format that could be transmitted via Wi-Fi. This involved configuring the analyzers to output vibration data in a compatible format (e.g., serial or analog output) that the ESP8266 could process. We developed code in Arduino C++ that handled data acquisition and Wi-Fi communication to send data on the cloud. The cloud data could then be accessed through an Android application (https://ergoaman1.web.app/#/), also available on desktop computers for further analysis. This system allows for continuous, remote monitoring of vibration data without requiring manual data collection. More details about the system can be found in the previous part of the publication (Singh et al., 2023c).

Taguchi's L_{27} orthogonal array was used to prepare a systematic experiment design, consisting of 27 experiment trial conditions (Singh et al., 2023c). Thus, a total of 405 experimental trials were performed by the five participants, who performed 27 experiments, with each experiment repeated three times. The WBV exposure to the tractor operators was recorded for a trial distance of 30 m, with each trial lasting approximately 38–50 s, depending on the speed range (0.6–0.8 m/s). This duration includes the time required for the machinery to accelerate and stabilize within the desired speed range before reaching the start of the 30-m measurement section. Start and end points were pre-marked on the field using visible reference points. Participants were instructed to maintain their preferred sitting posture throughout the trials, ensuring their back remained in contact with the seat's backrest. Vibration accelerations were recorded at the seat pan along the fore-and-aft (x), lateral (y), and vertical (z) axes during each experimental condition. The sampling rate was 6000 samples per second for each axis, and a total of 405 experiments were conducted. Given that each experiment lasted between 38 and 50 s, the total number of data samples collected ranged from approximately 228 million to 300 million, depending on the exact duration of each trial.

2.3. Ride features and feature engineering

This study includes three ride features: average speed (AS), pulling force (PF), and average tool depth (AD) (Singh et al., 2023b, 2023c). Participants were instructed to maintain the mean speed of the tractor between 0.6 and 0.8 m/s. The Bureau of Indian Standards recommended this speed for rotary tilling operations. Rotary tilling required a pulling force of 2, 4, or 6 kN, depending on terrain conditions. The pulling force was determined using a dynamometer attached between the tractor and rotary tiller (Singh et al., 2019). The depth of operation were 0.10 m, 0.12 m, and 0.14 m, respectively, for pulling forces of 2, 4, and 6 kN. The target variable, i.e., S_{ed}, was evaluated under different input conditions. The S_{ed} represents the mean daily dose of peak acceleration values experienced at the lumbar spine. The procedure for evaluating S_{ed} is presented in detail in ISO 2631-5 (2018) and in previous publications (Singh et al., 2022).

The original dataset contains three input features: AS, AD, and PF, with S_{ed} as the target variable. The featured engineering was performed to create further derived features from the original to capture potential nonlinear relationships and interactions between the original features. This step is important for capturing complex relationships in the data that may not be apparent in the original features. It was assumed that the combined effect of two features might be more informative than their individual effects. Therefore, three new interaction terms, AS × AD, AS × PF, and AD × PF were generated by multiplying pairs of original features. These interaction terms were added to the original feature set to expand the input space from three to six features. This step included feature analysis and selection to identify the most informative predictors in developing S_{ed} prediction model. The Pearson correlation matrix for all six features was calculated (Peng et al., 2005). This correlation analysis helped to identify potential multicollinearity issues and provided insights into the linear relationships between features. The mutual information regression method was employed to quantify the statistical dependency that helped capture both linear and nonlinear relationships between the features and the target variable based on the computed mutual information scores (Gong et al., 2024; Peng et al., 2005). The correlation analysis helped identify potential redundancies and interactions between features, while the mutual information-based selection helped identify the most informative features for the target variable, potentially capturing nonlinear relationships that correlation analysis might have missed. The features with higher mutual information scores were selected to contribute as informative predictors to improve the performance and interpretability of subsequent modeling steps.

2.4. Prediction modeling

2.4.1. Linear and ensemble models

Two model categories, i.e., classical linear and advanced ensemble methods, were developed and compared to predict the S_{ed} in the present study. Linear Regression (LR) was employed for linear models, which assumes a direct linear relationship between features and the target variable, and Huber Regression (HR) to mitigate the impact of outliers (Feng and Wu, 2022). These models served as a baseline to further compare with ensemble models. Five advanced techniques i.e., Random Forest (RF), Extra Trees (ET), Gradient Boosting (GB), XGBoost (XG), AdaBoost (AB), and Bagging (BG) Regressor was, used for ensemble models (González et al., 2020). Random Forest and Extra Trees Regressors were implemented with 100 estimators each, leveraging the power of multiple decision trees with different splitting strategies.

Gradient Boosting and XGBoost Regressors, also with 100 estimators, were employed for their ability to sequentially improve predictions by correcting errors in previous trees. Additionally, the AdaBoost Regressor with 50 estimators and the Bagging Regressor with 10 estimators were incorporated to reduce variance through random subsets of the data. All models were trained on the same features selected using mutual information scores to ensure fair comparison.

2.4.2. Development of meta-models

Meta models leveraged the strength of multiple base models, including linear and ensemble models. Separate meta-models were developed for linear models, integrating LR and HR, and for ensemble models, by integrating RF, ET, GB, XG, AB, and BG. Each meta-model had two different learners, i.e., RF and GB, resulting in four meta-models, two for the linear models and two for the ensemble models. Both meta-learners were set up with 50 estimators, providing sufficient capacity to learn from diverse base model predictions while maintaining reasonable training and prediction times. In RF, each estimator represents a decision tree, whereas in GB, it represents a boosting stage. This configuration allows the meta-models to capture complex data relationships without overfitting. The stacking process begins with cloning the base models to ensure independence and prevent data leakage. Meta-features were generated using Leave-One-Out cross-validation by training each base model on all but one sample and predicting the held-out sample (Varoquaux et al., 2017). This was repeated for all samples, which resulted in out-of-fold predictions that formed the meta-features. The meta-model training involved four key steps: cloning and preparing base models, thus generating meta-features through cross-validation by training each base model on the entire dataset and training the meta-model (RF and GB) on the generated meta-features. The fitted base models generated meta-features from input data during prediction. The trained meta-models were used to produce the final prediction. This multi-layered approach captures complex patterns potentially missed by individual models (Jiang et al., 2024). By developing separate meta-models for linear and ensemble base models, different model complexities were explored, which affected the final predictions, thus providing a robust framework for integrating diverse techniques and improving Sed's predictive performance.

2.4.3. Meta-modeling using ensemble learning approaches

After developing meta-models based on both linear and ensemble base models, it was recognized that combining them could improve predictive performance (Figueroa, 2024). This meta-ensemble approach was motivated by two key reasons. First, it aimed to take advantage of the strengths of each meta-learning algorithm (Manjunatha and Tsiotras, 2023), potentially capturing more complex patterns in predicting S_{ed}. Second, combining the meta-models was intended to reduce bias and variance, resulting in more stable and generalizable predictions (Ganaie et al., 2022). Four different methods were used separately to the linear and ensemble meta-models to develop meta-ensembling models, including simple averaging (SA), weighted averaging (WA), stacking with linear regression (SLR), and voting regressors (VR) (Ganaie et al., 2022). In simple averaging, the mean of predictions was calculated from both meta-models. Weighted average assigned equal weights of 0.5 for prediction. LR as a final layer was used for stacking to learn optimal combinations of meta-model predictions. The VR combined RF and GB estimators to make predictions based on majority voting. The performance of these methods was compared to obtain the optimum ensembled model.

2.5. Model evaluation, hypertuning and bootstrap analysis

The dataset consisted of 405 S_{ed} measurements, with each measurement representing the average Sed response for an individual experiment trial. To ensure a balanced and unbiased evaluation, we split the dataset into 284 training samples (70 %) and 121 testing samples (30 %), a commonly used ratio in machine learning to optimize bias-variance trade-off. Before training, we applied standard preprocessing techniques, including data normalization and outlier removal, to enhance data consistency. We employed the Leave-One-Out (LOO) cross-validation strategy for model validation (Varoquaux et al., 2017). The hyperparameters for each model are shown in Appendix 1. Bayesian optimization to fine-tune model parameters was used to improve performance (Singh et al., 2023c). The models were evaluated based on a set of performance metrics, namely mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), and coefficient of determination (R^2). The MAE, MSE, and RMSE quantify prediction errors. Lower values of the performance matrix indicate superior performance. MAE measures the mean absolute difference between predicted and actual values. MSE emphasizes larger errors by squaring differences. RMSE provides an error metric. R^2 indicates the proportion of variance in the target variable explained by the model. The values of the R^2 closer to 1 suggest a better fit. The mean percentage error rate was also calculated as a normalized measure of prediction error relative to actual values.

The stability and reliability of the models were tested through bootstrap analysis (Bhutamapuram and Sadam, 2022). Bootstrap is a statistical technique that allows for the empirical estimation of the sampling distribution of a statistic. Specifically, bootstrap resampling was applied by creating 1000 resamples of the original dataset with replacement. The models and their calculated R^2 values were retrained for each resample, which provided a distribution of R^2 estimates for each model. This approach enabled a more reliable estimate of the true performance metrics of the models than a single calculation on the original dataset. The 95 % confidence intervals (CIs) were calculated using the percentile method, where the lower and upper bounds correspond to the 2.5th and 97.5th percentiles of the bootstrap distribution (Bhutamapuram and Sadam, 2022; Henderson, 2005). Narrow CIs of the models show high stability, which suggests consistent predictive performance across different subsets of the data. Conversely, wider intervals suggest greater variability and sensitivity to the specific data points used for training.

2.6. Model interpretability

Permutation-based feature importance analysis, an Explainable AI approach, was used to interpret the influence of each input feature on the model's predictive performance (Kumar and Taylor, 2024). This method involves randomly shuffling individual features and measuring the resulting change in model accuracy, which provides insights into each feature's relative importance. This analysis reveals the relative significance of each feature in predicting S_{ed}. Thus, it is easy to identify the most influential factors in the model. The analysis was further extended to examine the importance of base models within the ensemble. This involved assessing base models' univariate, bivariate and multivariate impact in contributions to the ensembled meta-model. It allowed us to identify the models and their combinations to achieve optimal predictive accuracy for S_{ed}.

2.7. Software

MATLAB R2024a was used for data analysis and ML tasks. Key toolboxes included '*Statistics and ML Toolbox*' for implementing various regression models, cross-validation, and performance metrics. The '*fitlm*', '*fitrensemble*' and '*fitrsvm*' were employed for linear regression, 'ensemble methods like Random Forest and Gradient Boosting, and for Support Vector Regression, respectively. Cross-validation was implemented using the '*crossval*' function with Leave-One-Out method. The '*fscmrmr*' function performed minimum redundancy and maximum relevance (mRMR) for feature selection. Performance metrics were calculated using built-in functions like '*mse*' for MSE and i*rsquared*' for R^2 values.

3. Results and discussion

3.1. Descriptive and statistical analysis

The results showed a mean S_{ed} value of 0.55 MPa with a standard deviation of 0.11 MPa. The range of S_{ed} varied from 0.35 MPa to 0.790 MPa with an interquartile range (IQR) of 0.16 MPa. The distribution of S_{ed} was slightly right-skewed (skewness: 0.37) and platykurtic (kurtosis: −0.56), indicating a flatter-than-normal distribution.

Correlation analysis revealed significant relationships between operational parameters and S_{ed}. A strong positive correlation was observed between AS and S_{ed} ($R = 0.77$, $p < 0.00001$), indicating that higher speeds substantially increase the vibration experienced by the operators. These findings align with the fundamental principles of vibration mechanics, where higher operational speeds correspond to increased vibration magnitude transmitted through the vehicle chassis. AD showed a moderate negative correlation with S_{ed} ($R = -0.54$, $p < 0.01$). This inverse relationship may be due to a damping effect from soil engagement, where deeper penetration by the rotary tiller increases cutting force and dampens oscillation, reducing vibration magnitude. It is also possible that soil type and conditions not captured in the current dataset influenced this relationship. PF exhibited a weak positive correlation with S_{ed} ($r = 0.14$, $p > 0.05$). While increased pulling force slightly raised vibration levels, the effect was insignificant compared to the influence of speed and tool depth. This suggests that the tractor's engine and transmission system may effectively isolate much of the additional vibration generated by increased pulling forces.

Linear regression analysis further confirmed the results of the study. AS emerged as the strongest predictor of S_{ed} ($R = 0.77$, $p < 0.00001$). It was observed that for every unit increase in mean speed, S_{ed} increased by approximately 1.06 MPa, emphasizing the important role of speed management in mitigating health risks associated with WBV. The negative relationship between AD and S_{ed} (slope $= -3.72$, $R^2 = 0.29$, $p < 0.01$) reinforces the earlier correlation findings. The relationship between the PF and S_{ed} was weak and insignificant ($R^2 = 0.02$, $p = 0.4777$). Interaction between AS and PF showed a moderate positive relationship with S_{ed} ($R^2 = 0.14$, p = 0.0509). This suggests that the combined effect of speed and pulling force may be more relevant than pulling force alone. Other interactive terms (AS × AD, AD × PF, and AS × AD × PF) demonstrated weak relationships with S_{ed} and were not significant.

ANOVA test result ($F = 104.56$, $p < 0.00001$) provided strong evidence that the combined effect of all variables significantly influences S_{ed}. The model, incorporating all variables and their interactions, significantly improved the prediction of S_{ed}, except for the three-way interaction term (AS × AD × PF), which did not significantly contribute to the model's performance. This suggests that while the full model improves prediction, the highest-order interaction term did not add meaningful explanatory power.

3.2. Model performance and reliability

The results of the model performance metrics (MSE, RMSE, R2, and MAE) are presented in Fig. 2. In addition, the results of the Bootstrap analysis (used to assess the model's stability and confidence) are shown in Fig. 3.

In Fig. 2, the blue bars represent the performance of the regression models. The LR model achieved an R^2 of 0.88, explaining 88.27 % of the variance in S_{ed}. The RMSE was 0.03, and the MAE was 0.02. The bootstrap R^2 value was 0.91 (95 % CI: 0.87–0.94), indicating consistent performance across different data subsets. However, the model showed

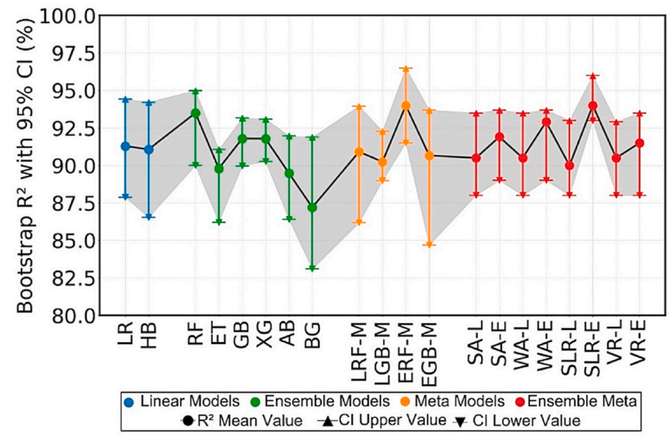

Fig. 3. Bootstrap stability analysis across various models.

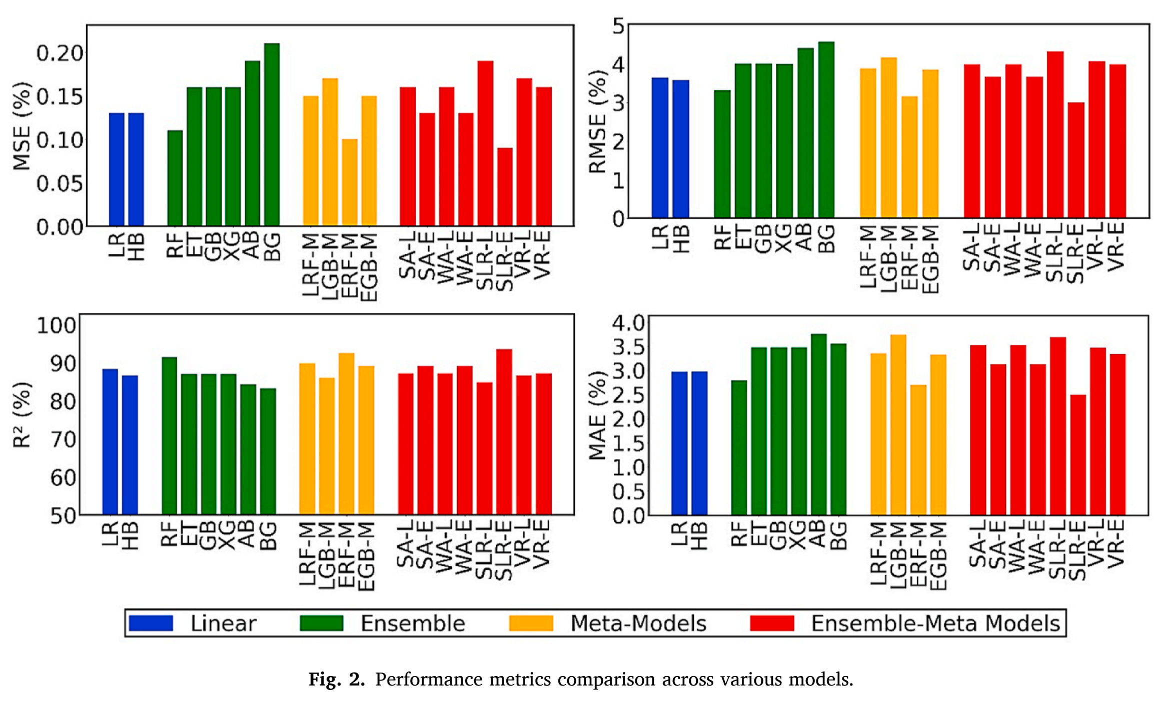

Fig. 2. Performance metrics comparison across various models.

slightly lower performance with an R^2 of 0.86 and an RMSE of 0.03. The MAE of 0.02 was comparable to that of the LR model, suggesting similar accuracy in absolute terms. The bootstrap R^2 of 0.91 (95 % CI: 0.86–0.94) suggests that the HR model exhibited good metrics, though its overall performance and stability were marginally lower than the standard LR model. These results highlight that while linear models provide a baseline, capturing more complex relationships within the data may be possible.

Among ensemble models (green bars), the RF model outperformed the other models with an R^2 of 0.91, an RMSE of 0.03, and an MAE of 0.02. The bootstrap R^2 of 0.93 (95 % CI: 0.90–0.95) indicates high performance and stability, making the RF model a robust choice for this specific dataset. The GB and XG models showed similar performance levels, with R^2 values of around 0.87 and RMSE values of approximately 0.04. Their identical MAEs of 0.03 suggest comparable accuracy in absolute terms. Bootstrap results (GB: $R^2 = 0.91$, 95 % CI: 0.89–0.93; XGBoost: $R^2 = 0.91$, 95 % CI: 0.90–0.93) indicate high stability, with XGBoost showing a slightly narrower CI. The Extra Trees (ET) model achieved an R^2 of 0.87, an RMSE of 0.04, and an MAE of 0.03. Bootstrap R^2 of 0.89 (95 % CI: 0.86–0.91) suggests good performance, though it demonstrates lower stability than the RF and boosting algorithms (GB and XG). The AB and BG models performed less than other ensemble models, with R^2 values of 0.84 and 0.83, respectively. Their higher RMSE values (0.04 for both) and MAEs (0.03 for both) indicate less accurate predictions. The bootstrap results (AB: $R^2 = 0.89$, 95 % CI: 0.86–0.91; BG: $R^2 = 0.87$, 95 % CI: 0.83–0.91) suggest lower stability, particularly for the BG model.

Overall, the best performance of the RF model among ensemble models, compared to the linear models (LR and HB), indicates that predictive performance benefits more from methods that reduce variance through aggregation of multiple decision trees. This approach effectively captures complex and nonlinear relationships in the data while mitigating overfitting. Thus, ensemble models, particularly RF, emerge as effective models for improving prediction accuracy and stability. Furthermore, the Meta-models demonstrated the potential to improve the predictive performance of linear and ensemble models, such as combining LR and HB – regression models; and RF, ET, GB, XG, AB, and BG – ensemble models), as shown in the subsequent paragraph.

Among Meta-models (yellow bars), the RF learner-based ensemble meta-model (ERF-M) achieved the highest R^2 of 0.92 and the lowest RMSE of 0.03 compared to individual regression (LR, HB in *blue bars*), ensemble models (RF, ET, GB, XG, AB, and BG in *green bars*) and meta-models (RF learner based linear meta-model – LRF-M; GB learner based linear meta-model – LGB-M; GB learner based ensemble meta-model – EGB-M, in *yellow bars*). ERF-M model's MAE of 0.02 shows exceptional predictive accuracy. Bootstrap R^2 of 0.94 (95 % CI: 0.91–0.96) indicates both high performance and significant stability; therefore, this meta-modeling approach effectively leverages the strengths of its constituent base models. The LRF-M also performed better, with an R^2 of 0.89, RMSE of 0.03, and MAE of 0.03. Bootstrap R^2 of 0.90 (95 % CI: 0.86–0.93) demonstrates the substantial performance of the LRF-M model; however, it shows slightly less stability than the ERF-M model. The LGM-M model achieved an R^2 of 0.86 with an RMSE of 0.04 and MAE of 0.03. Its bootstrap R^2 of 0.90 (95 % CI: 0.88–0.92) indicates reasonable performance; however, it shows less stability than the other meta-models.

These results highlight the potential of meta-modeling approaches, particularly those incorporating RF as meta learner, to capture complex relationships in predicting S_{ed} that individual models might miss. To further enhance model performance, the linear (LRF-M, LGB-M) and ensemble (ERF-M, EGB-M) meta-models were integrated using four ensemble learning procedures, as demonstrated in the following paragraph.

In Fig. 2, the red bars show the performance of linear (L) and ensemble (E) meta-models based on simple averaging (SA-L, SA-E), weighting averaging (WA-L, WA-E), stacking with linear regression (SLR-L, SLR-E) and voting regression (VR-L, VR-E). In results, SLR-E emerged as the best-performing procedure, achieving a relatively high R^2 of 0.93 and a lower RMSE of 0.03. The MAE of 0.02 indicates strong predictive accuracy. The bootstrap R^2 of 0.94 (95 % CI: 0.93–0.96) shows high performance and stability, suggesting that the stacking procedure effectively combines the strengths of ensemble based meta-models. SA-L and WA-L models exhibited identical model performance with R^2 of 0.87, RMSE of 0.03, MAE of 0.035 and bootstrap R^2 of 0.90 (95 % CI: 0.88–0.93). On the other hand, SA-E and WA-E outperformed SA-L and WA-L, with R^2 of 0.89 and bootstrap R^2 of 0.92 (95 % CI: 0.89–0.93). SLR-L model showed least performance compared to other models. Lastly, VR-L and VR-E models showed moderate performance, with VR-E achieving R^2 of 0.87, bootstrap R^2 of 0.91 (95 % CI: 0.88–0.93) and slightly outperformed VR-L that showed R^2 of 0.86 and bootstrap R^2 of 0.90 (95 % CI: 0.87–0.93). The voting procedure still improved some individual models, highlighting the potential benefits of combining different models.

This analysis provides essential insights into the comparative performance of classical models, ensemble methods, and meta-modeling techniques within predictive analytics. Classical models (LR and HB) attained acceptable predictive accuracy. However, their inherent limitations in capturing complex, nonlinear relationships in the dataset are evident due to their lower R^2 values relative to ensemble models. On the bright side, ensemble models substantially enhance predictive performance. RF model demonstrates high efficacy while maintaining consistent stability. Meta modeling exhibits an important advancement in predictive modeling. It combines the strengths of both linear and ensemble methods. ERF-M demonstrates increased model performance compared to individual classical and ensemble models. Further, the ensemble learning procedures, mainly SLR-E show its effectiveness in maximizing model performance by outperforming all the models.

3.3. Feature importance analysis

Feature importance analysis exhibits the multi-dimensional (univariate, bivariate, and multivariate) impact of operating parameters (AS, PF and AD) contributing to the impact S_{ed}. It also assesses the multi-dimensional contributions of models used to develop SLR-E model in predicting S_{ed}, as shown in Fig. 4. The AS emerges as the most impactful parameter for predicting $S_{ed,}$ with an importance score of 0.58. This indicates that the tractor's speed significantly affects lumbar spine stress, as higher speeds are associated with increased vibration magnitudes. Previous studies have also found AS to be a critical factor in vibration exposure, demonstrating that increased speed amplifies vibration transmission, enhancing the S_{ed} response (Singh et al., 2019).

The interaction between AS and PF ranks as the second most important feature, with an importance score of 0.40. This suggests that the combined effects of speed and the force needed to pull the rotary tiller are vital in determining lumbar spine stress. Specifically, the influence of speed on S_{ed} is moderated by the resistance faced during rotary tilling. AD is the third most influential parameter, with a score of 0.32. In contrast, PF and the interaction between AS and AD show relatively low importance scores (approximately 0.1) when considered individually. While PF has limited significance, its interaction with AS (i.e., AS × PF) highlights its increased relevance when combined with the tractor's speed. Thus, PF should not be ignored, especially when combined with AS. A combination of RF, ET, GB, XG, AB, and BR consistently showed the highest importance scores of 0.99. These models collectively contribute significantly to the predictive performance of the meta-models. Notably, combinations that included five out of these six models maintained near-perfect importance scores (0.92), indicating their critical role in effectively capturing the complexities of the data.

Combinations that excluded more than one of these models experienced a slight decline in importance, averaging around 0.80. A further reduction in the number of models led to a more noticeable drop in importance scores, with pairs averaging around 0.4 and individual

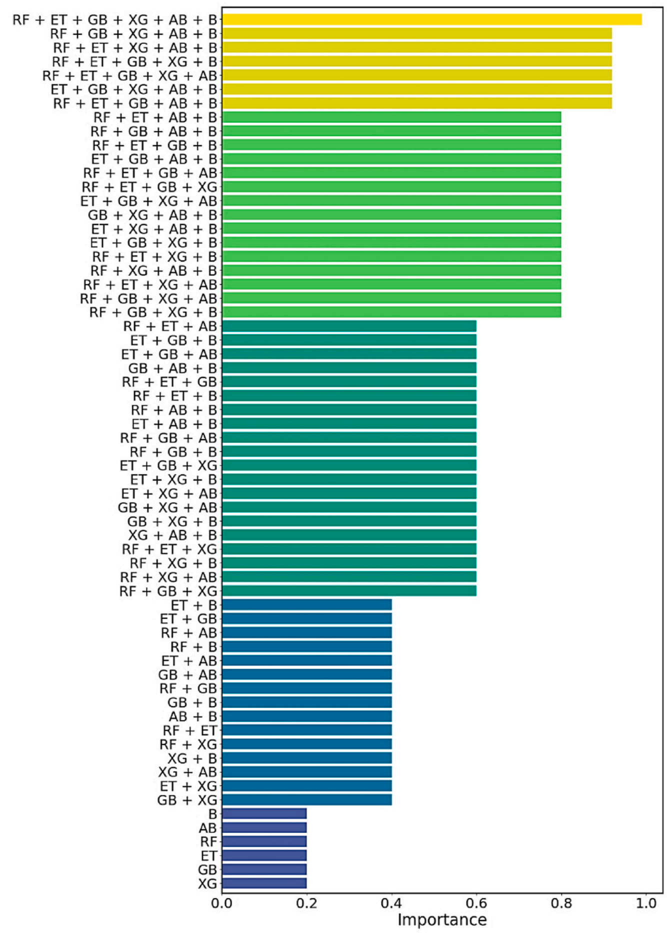

Fig. 4. Feature importance analysis across univariate, bivariate, and multivariate combinations of the base model used to develop SLR-E.

models around 0.2. These findings underscore the value of employing multiple ensemble methods to enhance predictive accuracy and stability within the meta-model. They also emphasize the importance of diversity in model selection for achieving optimal performance.

4. Discussion and implications

This study provides information on several essential aspects of S_{ed} assessment and its prediction in real-field rotary tillage operations. It examines the contributions of operational factors such as speed, pulling force, and tillage depth to influencing S_{ed}. The study compares classical prediction models with ensemble-based approaches, showing that ensemble methods lead to improved accuracy due to their ability to capture complex, nonlinear relationships among variables. Meta-modeling and ensemble learning techniques enhance model performance by combining multiple learning algorithms to improve predictive power and generalization. Additionally, feature importance analysis helps clarify the contributing role of base models within the ensemble framework in Sed prediction.

The role of tractor speed in impacting S_{ed} highlights the necessity for effective speed management strategies. Increased speed results in greater WBV exposure (Kumar et al., 2001; Scarlett et al., 2007; Servadio et al., 2007; Singh et al., 2019), leading to higher S_{ed}. Higher speeds amplify the dynamic interactions between the tractor and the terrain, increasing the vibrational accelerations transmitted through the tractor's chassis and, ultimately to the operator's spine. Moreover, this relationship is consistent with the principles of vibration mechanics, where higher velocities lead to increased excitation frequencies and amplitudes, resulting in greater oscillation magnitudes. This finding is also consistent with the study for small vehicles (Grami et al., 2019). Furthermore, tillage depth demonstrates a moderate negative relationship with S_{ed}. The inverse relationship between tillage depth and S_{ed} suggests that deeper tillage may enhance the damping characteristics of the soil-machine system (Ahmadian et al., 2021). This damping effect possibly arises from increased soil resistance and cutting forces encountered at greater depths, which absorb and dissipate vibrational energy more effectively by providing greater mechanical impedance between the tractor and the soil (Singh et al., 2019). This phenomenon highlights the potential for optimizing tillage practices for agronomic benefits and improving operator comfort and reducing health risks. The complex balance between operational efficiency and operator safety becomes evident, indicating that deeper tillage, within agronomic limits, could serve as a practical intervention to attenuate WBV exposure. Further investigation into the soil-structure interaction during deep tillage could provide insights into designing implements that minimize vibration transmission. Further research is essential to explore the interactions among soil properties, tillage implements, and vibration transmission. Investigating a broader range of soil types and moisture conditions will provide valuable insights into how different factors affect vibration transmission, leading to more effective strategies for minimizing vibration in agricultural practices. Although pulling force alone showed a minimal direct impact on S_{ed}, its interaction with operating speed revealed a more substantial effect. This interaction suggests that the mechanical demands placed on the tractor during operations involving higher pulling forces and speeds can mutually elevate vibration levels experienced by the operator. The tractor's engine and transmission systems, while effective at isolating vibrations from pulling forces under normal conditions, may become less efficient when compounded by increased speeds. This information emphasizes the importance of considering combined operational parameters rather than isolated factors when assessing WBV exposure risks. Moreover, as tractors operate under varying conditions, the implications of this relationship extend towards strategies such as enhancing the mechanical properties of suspension systems, employing advanced vibration-damping technologies, and optimizing operational parameters to reduce WBV exposure.

From a predictive modeling perspective, this study demonstrates the dominance of ensemble models over classical linear models in capturing the complex, nonlinear interactions between operational parameters and S_{ed}. This study demonstrates the capability of an RF-based meta-learner to enhance prediction accuracy and stability. The SLR-E based ensemble learning procedure particularly shows its ability to develop an effective S_{ed} prediction framework. This method allows the model to detect subtle, nonlinear interactions between factors such as tractor speed, pulling force, and tillage depth, all of which directly impact the S_{ed} levels experienced by operators. The model effectively compensates for individual models' limitations by combining their strengths, leading to more reliable S_{ed} predictions under varying operational conditions. The practical implications of this modeling framework are significant. Agricultural environments are highly dynamic, with rapidly changing conditions such as soil type, moisture, and equipment settings influencing vibration exposure. Simple linear models may fail to account for these complexities, but ensemble models such as RF and stacking methods excel by identifying patterns that may not be immediately apparent. For example, fluctuations in tractor speed or sudden changes in pulling force due to soil inconsistencies can lead to elevated WBV levels.

In addition, applying feature importance analysis is important in interpreting the contribution of various base models that form the SLR-E model. It directly informs which models are most effective for S_{ed} prediction and whether their inclusion justifies the computational cost. This study highlights that the SLR-E model benefits significantly from the collective contribution of all base models—Random Forest, Extra Trees, Gradient Boosting, XGBoost, AdaBoost, and Bagging. The findings show that excluding these models leads to a noticeable decline in predictive accuracy, confirming that their combined use is essential for achieving the best performance. This result suggests that reducing the number of models would compromise the system's ability to capture the complex interactions inherent in S_{ed} prediction. Therefore, including all base models maximizes prediction accuracy, justifying their role in the ensemble despite the added computational complexity (Ganaie et al., 2022).

From an application standpoint, the ensemble model, with its ability to learn from these complex interactions, ensures more accurate real-time S_{ed} predictions. This enhanced predictive capability is essential for developing intelligent, proactive safety systems. Incorporating intelligent speed adaptation systems into this framework can provide a comprehensive solution. Such systems could adjust tractor ride parameters based on real-time vibration feedback, ensuring that S_{ed} levels remain within safe limits. For example, Singh et al. (2023a) introduced an IoT-based solution (ThingSpeak enabled) to monitor real-time WBV levels and issue immediate alerts when vibrations exceed recommended thresholds. This system could be further improved by integrating real-time S_{ed} monitoring, allowing for dynamic adjustments in tractor speed, tillage depth, or other operational parameters to continuously maintain operator safety without compromising productivity. Moreover, the predictive model could be integrated into tractor control systems, enabling automated adjustments to operational parameters based on terrain and task-specific requirements. This integration opens possibilities for developing autonomous or semi-autonomous tractors with advanced safety features, enhancing efficiency and operator well-being.

Integrating advanced ML models into real-time systems could significantly enhance occupational safety by reducing the risk of musculoskeletal disorders associated with WBV exposure. These systems eliminate the need for constant manual intervention, helping maintain safety standards under varying agricultural conditions. Furthermore, the data collected from these systems can inform policy decisions and establish more accurate exposure limits tailored to specific agricultural tasks and environments. Furthermore, the model's adaptability makes it valuable for immediate risk management and long-term prevention strategies, aligning with international standards such as ISO 2631-5. Future research could explore integrating biomechanical models of the human body to better understand the impact of WBV on different body segments, enhancing the predictive capability of S_{ed} models. Developing personalized models considering operator-specific factors such as body mass index and posture could further refine risk assessments.

Implementing such advanced predictive systems also presents opportunities for collaboration between agricultural engineers, data scientists, and occupational health experts. Interdisciplinary research could develop comprehensive guidelines and best practices for vibration exposure management in agriculture. In a nutshell, adopting ensemble-based predictive models for S_{ed} improves the accuracy of WBV exposure assessments. It paves the way for innovative solutions to enhance operator safety, optimize agricultural operations, and inform regulatory frameworks.

5. Conclusions, limitations and future research direction

The study emphasizes that controlling operational speed is paramount in reducing WBV exposure and associated health risks in tractor operators. Adjusting agricultural depth and managing the interaction between speed and pulling force can mitigate vibration levels. Among the tested models, the RF model performed best as an individual predictor (R^2 of 0.91), while the RF-based meta-learner further improved accuracy (R^2 of 0.92). Furthermore, stacking ensemble model (i.e., SLR-E) outperformed all others (R^2 of 0.93). This clearly demonstrates that aggregating multiple ensemble learners (RF and GB) enhances predictive accuracy and robustness. These results significantly contribute to existing literature by demonstrating practical and highly effective strategies (multimodal ensemble approach) for predicting S_{ed} in agricultural contexts.

Despite these contributions, the study has certain limitations. Key operational factors such as tractor speed, pulling force, and tillage depth were analyzed, but other elements, including soil strength, terrain variability, and tillage implement types were not considered. Future research should expand operational parameters to improve model robustness and applicability across diverse agricultural settings. Additionally, the study's dataset was constrained to a single tractor and five operators, limiting the generalizability of results. Incorporating multiple tractor models, larger operator samples, and varied geographic conditions would enhance model training and validation, ensuring wider applicability. Moreover, operator-specific characteristics (e.g., posture, anthropometry) influence WBV exposure but were not included. Future studies should integrate biomechanical and human-centric variables for personalized risk assessments. On a positive note, a recent study successfully tested similar ensemble models (as used in the present study) for predicting head vibrations based on different driving and seating conditions, demonstrating the relevance of ensemble techniques in vehicle dynamics (Singh et al., 2025). The multimodal framework introduced in this study presents an advanced application of ensemble modeling, with strong potential for predicting WBV-related parameters. Further validation, refinement, and adaptation for occupational health applications are encouraged.

The current study employed two classical models (Linear and Huber Regression), five ensemble models (RF, Extra Trees, Gradient Boosting, XGBoost, AdaBoost, Bagging), and two meta-learners (RF and GB). While the SLR-E model combined these six ensemble models, future research should explore advanced ensemble methods such as LightGBM (Yan et al., 2019), CatBoost (Antypas et al., 2022), and other recently developed algorithms. Additional meta-learners such as Multi-Layer Perceptron (Al Bataineh et al., 2022), Blending Regressor (Chatzimparmpas et al., 2021) and Stacked Ensemble (Zian et al., 2021) should also be investigated. Evaluating these models and meta-learners is important, as a smaller set of models with comparable or better performance reduces computational complexity. This enhances the SLR-E model's scalability for real-time agricultural predictions, enabling faster and more efficient decision-making while ensuring accuracy.

Explainability is another key challenge. This study relied on feature importance as an Explainable AI method. However, alternative techniques such as Shapley Additive Explanations (SHAP) (Al-Najjar et al., 2023), Local Interpretable Model-agnostic Explanations (LIME) (Zafar and Khan, 2021) and Partial Dependence Plots (Ryo, 2022) may also be tested to further enhance transparency and trustworthiness of predictive models. The key difference between feature importance and methods such as SHAP and LIME lies in the level of interpretability they provide. While feature importance offers a global view of feature impacts across all predictions, SHAP and LIME provide local explanations for individual predictions. Integrating these advanced methods into the modeling process will significantly enhance the practical interpretability and acceptability of predictive models, making them more applicable in real-world scenarios where understanding the underlying mechanics of predictions is as important as the predictions themselves.

In addition to ensemble modeling, hybrid models that integrate ensemble techniques with deep learning approaches (e.g., Convolutional Neural Networks and Long Short-Term Memory networks) could enhance S_{ed} predictions by capturing spatial and temporal dependencies in WBV data. Such models would be particularly valuable for real-time monitoring, where balancing accuracy, efficiency, and scalability is crucial for agricultural operations.

As AI-driven predictive models scale up, addressing computational complexity and its impact on processing speed, energy consumption, and sustainability becomes important. High-complexity models may require greater computational power, leading to delays (latency) in real-time predictions and increasing carbon emissions. If models consume excessive energy, they could pose a sustainability challenge, particularly in resource-intensive applications. Future studies should investigate strategies to optimize model efficiency without sacrificing accuracy. Techniques such as model compression, adaptive learning, and Green AI approaches could help develop more sustainable predictive systems. While this study does not yet explore these aspects due to data limitations, future research should integrate scalability and energy efficiency considerations to ensure practical and responsible AI deployment.

CRediT authorship contribution statement

Amandeep Singh: Writing – original draft, Software, Methodology, Formal analysis, Conceptualization. **Naser Nawayseh:** Writing – review & editing, Methodology, Conceptualization. **Philippe Doyon-Poulin:** Writing – review & editing, Data curation. **Stephan Milosavljevic:** Writing – review & editing, Supervision. **Krishna N. Dewangan:** Writing – review & editing, Software, Methodology. **Yash Kumar:** Software. **Siby Samuel:** Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

Appendix 1
Hyperparameter Specifications from Base Models to Ensemble Meta Models

Model	Method	Hyperparameters
Linear Models	LR	fit_intercept: True, copy_X: True, n_jobs: None, positive: False
	HR	epsilon: 1.35, alpha: 0.0001, fit_intercept: True, max_iter: 100, tol: 1e-05
Ensemble Models	RF	n_estimators: 100, criterion: 'squared_error', max_features: 'auto', bootstrap: True, min_samples_split: 2, min_samples_leaf: 1, random_state: 42
	ET	n_estimators: 100, criterion: 'squared_error', max_features: 'auto', bootstrap: False, min_samples_split: 2, min_samples_leaf: 1, random_state: 42
	FB	n_estimators: 100, learning_rate: 0.1, max_depth: 3, loss: 'squared_error', subsample: 1.0, min_samples_split: 2, random_state: 42
	XGB	n_estimators: 100, learning_rate: 0.1, max_depth: 6, subsample: 1.0, colsample_bytree: 1.0, objective: 'reg:squarederror', random_state: 42
	AB	n_estimators: 50, learning_rate: 1.0, loss: 'linear', base_estimator: None, random_state: 42
	B	n_estimators: 10, max_samples: 1.0, max_features: 1.0, bootstrap: True, random_state: 42
Meta-Models	RF (ML)	n_estimators: 50, criterion: 'squared_error', max_depth: None, min_samples_split: 2, min_samples_leaf: 1, max_features: 1.0, bootstrap: True, random_state: 42
	GB (ML)	n_estimators: 50, learning_rate: 0.1, max_depth: 3, min_samples_split: 2, min_samples_leaf: 1, max_features: 1.0, loss: 'squared_error', random_state: 42
	RF (ME)	n_estimators: 50, criterion: 'squared_error', max_depth: None, min_samples_split: 2, min_samples_leaf: 1, max_features: 1.0, bootstrap: True, random_state: 42
	GB (ME)	n_estimators: 50, learning_rate: 0.1, max_depth: 3, min_samples_split: 2, min_samples_leaf: 1, max_features: None, loss: 'squared_error', random_state: 42
Meta-Ensembling	SA	N/A
	WA	weights: [0.5, 0.5]
	SLR	fit_intercept: True, copy_X: True, n_jobs: None
	VR	estimators: [('rf', RandomForestRegressor(n_estimators = 100, random_state = 42)), ('gbm', GradientBoostingRegressor(n_estimators = 100, random_state = 42))]

Note: *LR: Linear Regression; HR: Huber Regression; RF: Random Forest; ET: Extra Trees; GB: Gradient Boosting; XGB: XGBoost; AB: AdaBoost; B: Bagging; RF (ML): Random Forest based Meta-Linear Model; GB (ML): Gradient Boost based Meta-Linear Model; RF (ME): Random Forest based Meta-Ensemble Model; GB (ME): Gradient Boost based Meta-Ensemble Model; SA: Simple Averaging; WA: Weighted Averaging; SLR: Stacking with Linear Regression; and VR: Voting Regressor.*

Data availability

Data will be made available on request.

References

Abimannan, S., El-Alfy, E.-S.M., Chang, Y.-S., Hussain, S., Shukla, S., Satheesh, D., 2023. Ensemble multifeatured deep learning models and applications: a survey. IEEE Access 11, 107194–107217. https://doi.org/10.1109/ACCESS.2023.3320042.

Adams, B.T., Reid, J.F., Hummel, J.W., Zhang, Q., Hoeft, R.G., 2004. Effects of central tire inflation systems on ride quality of agricultural vehicles. J. Terramechanics 41, 199–207. https://doi.org/10.1016/j.jterra.2004.02.011.

Ahmadian, H., Najafi, G., Ghobadian, B., Hassan-Beygi, S.R., Hoseini, S.S., 2021. Evaluation of the combustion-induced noise and vibration using coherence and wavelet coherence estimates in a diesel engine. Int. J. Engine Res. 22, 827–846. https://doi.org/10.1177/1468087419878547.

Al Bataineh, A., Kaur, D., Jalali, S.M.J., 2022. Multi-layer perceptron training optimization using nature inspired computing. IEEE Access 10, 36963–36977. https://doi.org/10.1109/ACCESS.2022.3164669.

Ali, D., Frimpong, S., 2021. DeepImpact: a deep learning model for whole body vibration control using impact force monitoring. Neural Comput. Appl. 33, 3521–3544. https://doi.org/10.1007/s00521-020-05218-6.

Al-Najjar, H.A.H., Pradhan, B., Beydoun, G., Sarkar, R., Park, H.-J., Alamri, A., 2023. A novel method using explainable artificial intelligence (XAI)-based shapley additive explanations for spatial landslide prediction using time-series SAR dataset. Gondwana Research, Data driven models 123, 107–124. https://doi.org/10.1016/j.gr.2022.08.004.

AlShabi, M., Nawayseh, N., 2022. Using ANN to study the gender effect on horizontal transmissibility to the head during whole-body vibration, in: Artificial intelligence and machine learning for multi-domain operations applications IV. Presented at the Artificial Intelligence and Machine Learning for Multi-Domain Operations Applications IV, pp. 666–673. https://doi.org/10.1117/12.2632218. SPIE.

Antypas, E., Spanos, G., Lalas, A., Votis, K., Tzovaras, D., 2022. Estimated time of arrival in autonomous vehicles using gradient boosting: real-life case study in public transportation. In: 2022 IEEE International Smart Cities Conference (ISC2). Presented at the 2022 IEEE International Smart Cities Conference (ISC2), pp. 1–7. https://doi.org/10.1109/ISC255366.2022.9921853.

Benos, L., Bechar, A., Bochtis, D., 2020. Safety and ergonomics in human-robot interactive agricultural operations. Biosyst. Eng. 200, 55–72. https://doi.org/10.1016/j.biosystemseng.2020.09.009.

Bhutamapuram, U.S., Sadam, R., 2022. With-in-project defect prediction using bootstrap aggregation based diverse ensemble learning technique. J. King Saud Univ. Comput. Inf. Sci. 34, 8675–8691. https://doi.org/10.1016/j.jksuci.2021.09.010.

Bovenzi, M., Betta, A., 1994. Low-back disorders in agricultural tractor drivers exposed to whole-body vibration and postural stress. Appl. Ergon. 25, 231–241. https://doi.org/10.1016/0003-6870(94)90004-3.

Campagner, A., Ciucci, D., Cabitza, F., 2023. Aggregation models in ensemble learning: a large-scale comparison. Inf. Fusion 90, 241–252. https://doi.org/10.1016/j.inffus.2022.09.015.

Cao, Y., Geddes, T.A., Yang, J.Y.H., Yang, P., 2020. Ensemble deep learning in bioinformatics. Nat. Mach. Intell. 2, 500–508. https://doi.org/10.1038/s42256-020-0217-y.

Chakraborty, C., Bhattacharya, M., Pal, S., Lee, S.-S., 2024. From machine learning to deep learning: advances of the recent data-driven paradigm shift in medicine and healthcare. Current Research in Biotechnology 7, 100164. https://doi.org/10.1016/j.crbiot.2023.100164.

Chan, V.C.H., Ross, G.B., Clouthier, A.L., Fischer, S.L., Graham, R.B., 2022. The role of machine learning in the primary prevention of work-related musculoskeletal disorders: a scoping review. Appl. Ergon. 98, 103574. https://doi.org/10.1016/j.apergo.2021.103574.

Chang, M.K., Li, Y.F., Huang, H.W., 2011. Hazard of vibration and healthy risk assessment for domestic dump truck driver in Taiwan. Appl. Mech. Mater. 52–54, 186–191. https://doi.org/10.4028/www.scientific.net/AMM.52-54.186.

Chatzimparmpas, A., Martins, R.M., Kucher, K., Kerren, A., 2021. Empirical study: visual analytics for comparing stacking to blending ensemble learning. In: 2021 23rd International Conference on Control Systems and Computer Science (CSCS). Presented at the 2021 23rd International Conference on Control Systems and Computer Science (CSCS), pp. 1–8. https://doi.org/10.1109/CSCS52396.2021.00008.

Deprez, K., Moshou, D., Ramon, H., 2005. Comfort improvement of a nonlinear suspension using global optimization and in situ measurements. J. Sound Vib. 284, 1003–1014. https://doi.org/10.1016/j.jsv.2004.07.010.

Dewangan, K.N., Patel, T., Vidhu, K.P., Khumukcham, B.S., Lusang, I., Sumpi, N., Yudik, L., 2023. An investigation of the hand anthropometric database of agricultural workers and integration of the database into tools and protective gear designs. Work 74, 1461–1480. https://doi.org/10.3233/WOR-211238.

Eger, T., Stevenson, J., Boileau, P.-É., Salmoni, A., 2008. Predictions of health risks associated with the operation of load-haul-dump mining vehicles: part 1—Analysis of whole-body vibration exposure using ISO 2631-1 and ISO-2631-5 standards. International Journal of Industrial Ergonomics, Special Issue: Workplace Vibration Exposure Characterization, assessment and ergonomic interventions 38, 726–738. https://doi.org/10.1016/j.ergon.2007.08.012.

Fei, C.-W., Bai, G.-C., 2013. Wavelet correlation feature scale entropy and fuzzy support vector machine approach for aeroengine whole-body vibration fault diagnosis. Shock Vib. 20, 341–349. https://doi.org/10.3233/SAV-2012-00748.

Feng, Y., Wu, Q., 2022. A statistical learning assessment of Huber regression. J. Approx. Theor. 273, 105660. https://doi.org/10.1016/j.jat.2021.105660.

Figueroa, D.E., 2024. Ensemble learning methods and AI-Driven predictive models: fusion of models for enhanced change management and performance optimization. Journal of AI-Assisted Scientific Discovery 4, 251–262.

Ganaie, M.A., Hu, M., Malik, A.K., Tanveer, M., Suganthan, P.N., 2022. Ensemble deep learning: a review. Eng. Appl. Artif. Intell. 115, 105151. https://doi.org/10.1016/j.engappai.2022.105151.

Gong, H., Li, Y., Zhang, J., Zhang, B., Wang, X., 2024. A new filter feature selection algorithm for classification task by ensembling pearson correlation coefficient and mutual information. Eng. Appl. Artif. Intell. 131, 107865. https://doi.org/10.1016/j.engappai.2024.107865.

González, S., García, S., Del Ser, J., Rokach, L., Herrera, F., 2020. A practical tutorial on bagging and boosting based ensembles for machine learning: algorithms, software tools, performance study, practical perspectives and opportunities. Inf. Fusion 64, 205–237. https://doi.org/10.1016/j.inffus.2020.07.007.

Grami, S., Nawayseh, N., Hamdan, S., 2019. Effect of car speed on the transmission of vibration through the seat pan and backrest: field study. Int. J. Veh. Noise Vib. 15, 192–204. https://doi.org/10.1504/IJVNV.2019.106381.

Griffin, M.J., 2007. Discomfort from feeling vehicle vibration. Veh. Syst. Dyn. 45, 679–698. https://doi.org/10.1080/00423110701422426.

Hanumegowda, P.K., Gnanasekaran, S., 2022. Prediction of work-related risk factors among bus drivers using machine learning. Int. J. Environ. Res. Publ. Health 19, 15179. https://doi.org/10.3390/ijerph192215179.

Henderson, A.R., 2005. The bootstrap: a technique for data-driven statistics. Using computer-intensive analyses to explore experimental data. Clin. Chim. Acta 359, 1–26. https://doi.org/10.1016/j.cccn.2005.04.002.

Hota, S., Tewari, V.K., Chandel, A.K., 2023. Workload assessment of tractor operations with ergonomic transducers and machine learning techniques. Sensors 23, 1408. https://doi.org/10.3390/s23031408.

ISO 2631-1:1997, 2010. Mechanical Vibration and Shock — Evaluation of Human Exposure to whole-body Vibration — Part 1: General Requirements.

ISO 2631-5, 2018. Mechanical vibration and shock — evaluation of human exposure to whole-body vibration — part 5: method for evaluation of vibration containing multiple shocks. https://www.iso.org/obp/ui/en/#iso:std:iso:2631:-5:ed-2:v2:en, 6.24.24.

Jiang, K., Xiong, Z., Yang, Q., Chen, J., Chen, G., 2024. An interpretable ensemble method for deep representation learning. Eng. Rep. 6, e12725. https://doi.org/10.1002/eng2.12725.

Killen, W., Eger, T., 2016. Whole-Body Vibration: Overview of Standards Used to Determine Health Risks.

Krajnak, K., 2018. Health effects associated with occupational exposure to hand-arm or whole body vibration. J. Toxicol. Environ. Health, Part A B 21, 320–334. https://doi.org/10.1080/10937404.2018.1557576.

Kumar, A., Mahajan, P., Mohan, D., Varghese, M., 2001. IT—Information technology and the human interface: tractor vibration severity and driver health: a study from rural India. J. Agric. Eng. Res. 80, 313–328. https://doi.org/10.1006/jaer.2001.0755.

Kumar, A., Taylor, J.W., 2024. Feature importance in the age of explainable AI: case study of detecting fake news & misinformation via a multi-modal framework. Eur. J. Oper. Res. 317, 401–413. https://doi.org/10.1016/j.ejor.2023.10.003.

Langer, T.H., Ebbesen, M.K., Kordestani, A., 2015. Experimental analysis of occupational whole-body vibration exposure of agricultural tractor with large square baler. Int. J. Ind. Ergon. 47, 79–83. https://doi.org/10.1016/j.ergon.2015.02.009.

Lines, J., Stiles, M., Whyte, R., 1995. Whole body vibration during tractor driving. J. Low Freq. Noise Vib. Act. Control 14, 87–104. https://doi.org/10.1177/026309239501400204.

Lu, W., Wei, Y., Yuan, J., Deng, Y., Song, A., 2020. Tractor assistant driving control method based on EEG combined with RNN-TL deep learning algorithm. IEEE Access 8, 163269–163279. https://doi.org/10.1109/ACCESS.2020.3021051.

Manjunatha, H., Tsiotras, P., 2023. Beyond one model fits all: ensemble deep learning for autonomous vehicles. https://doi.org/10.48550/arXiv.2312.05759.

Marin, L.S., Rodriguez, A.C., Rey-Becerra, E., Piedrahita, H., Barrero, L.H., Dennerlein, J. T., Johnson, P.W., 2017. Assessment of whole-body vibration exposure in mining earth-moving equipment and other vehicles used in surface mining. Annals of Work Exposures and Health 61, 669–680. https://doi.org/10.1093/annweh/wxx043.

Mehta, C., Bangale, R., Chandel, N., Kumar, M., 2024. Farm Mechanization in India: Status and Way Forward, 54, pp. 75–88.

Mehta, C., Chandel, N., Jena, P., Jha, A., 2019. Indian agriculture counting on farm mechanization. Ama, Agric. Mech. Asia, Afr. Lat. Am. 50, 84–89.

Mehta, C.R., Tewari, V.K., 2010. Damping characteristics of seat cushion materials for tractor ride comfort. J. Terramechanics 47, 401–406. https://doi.org/10.1016/j.jterra.2009.11.001.

Mehta, C.R., Tewari, V.K., 2000. Seating discomfort for tractor operators – a critical review. Int. J. Ind. Ergon. 25, 661–674. https://doi.org/10.1016/S0169-8141(99)00054-2.

Milosavljevic, S., Mani, R., Ribeiro, D.C., Vasiljev, R., Rehn, B., 2012. Exploring how anthropometric, vehicle and workplace factors influence whole-body vibration exposures during on-farm use of a quad bike. Int. J. Ind. Ergon. 42, 392–396. https://doi.org/10.1016/j.ergon.2012.04.004.

Milosavljevic, S., Mcbride, D.I., Bagheri, N., Vasiljev, R.M., Mani, R., Carman, A.B., Rehn, B., 2011. Exposure to whole-body vibration and mechanical shock: a field study of quad bike use in agriculture. Ann. Occup. Hyg. 55, 286–295. https://doi.org/10.1093/annhyg/meq087.

Mohammed, A., Kora, R., 2023. A comprehensive review on ensemble deep learning: opportunities and challenges. J. King Saud Univ. Comput. Inf. Sci. 35, 757–774. https://doi.org/10.1016/j.jksuci.2023.01.014.

Nguyen, V.N., Inaba, S., 2011. Effects of tire inflation pressure and tractor velocity on dynamic wheel load and rear axle vibrations. J. Terramechanics 48, 3–16. https://doi.org/10.1016/j.jterra.2010.09.001.

Pei, Y., Song, Z., Jin, X., Zhao, D., 2019. Study on effort of attention allocation for tractor drivers in Head-Up display. IFAC-PapersOnLine, 14th IFAC Symposium on Analysis, Design, and Evaluation of Human Machine Systems HMS 2019 52, 294–298. https://doi.org/10.1016/j.ifacol.2019.12.117.

Peng, H., Long, F., Ding, C., 2005. Feature selection based on mutual information criteria of max-dependency, max-relevance, and min-redundancy. IEEE Trans. Pattern Anal. Mach. Intell. 27, 1226–1238. https://doi.org/10.1109/TPAMI.2005.159.

Prakash, C., Singh, L.P., Gupta, A., Singh, A., 2025. Prediction of hand-arm vibration among tractor operators in different soil tillage operations using artificial neural network-based model. Comput. Electron. Agric. 230, 109858. https://doi.org/10.1016/j.compag.2024.109858.

Rakheja, S., Dewangan, K.N., Dong, R.G., Marcotte, P., 2020. Whole-body vibration biodynamics - a critical review: I. Experimental biodynamics. International Journal of Vehicle Performance 6, 1–51. https://doi.org/10.1504/IJVP.2020.104493.

Ramar, K., Kumaraswamidhas, L.A., Balaji, P.S., Agasthian, A., 2023. Whole body vibration impact assessment on dumper operator using computational learning technique. Int. J. Precis. Eng. Manuf. 24, 219–238. https://doi.org/10.1007/s12541-022-00732-0.

Ryo, M., 2022. Explainable artificial intelligence and interpretable machine learning for agricultural data analysis. Artificial Intelligence in Agriculture 6, 257–265. https://doi.org/10.1016/j.aiia.2022.11.003.

Scarlett, A.J., Price, J.S., Stayner, R.M., 2007. Whole-body vibration: evaluation of emission and exposure levels arising from agricultural tractors. J. Terramechanics 44, 65–73. https://doi.org/10.1016/j.jterra.2006.01.006.

Servadio, P., Marsili, A., Belfiore, N.P., 2007. Analysis of driving seat vibrations in high forward speed tractors. Biosyst. Eng. 97, 171–180. https://doi.org/10.1016/j.biosystemseng.2007.03.004.

Singh, A., Nawayseh, N., Dhabi, Y.K., Samuel, S., Singh, H., 2023a. Transforming farming with intelligence: smart vibration monitoring and alert system. Journal of Engineering Research S2307187723002043. https://doi.org/10.1016/j.jer.2023.08.025.

Singh, A., Nawayseh, N., Rakheja, S., 2025. Ensemble modeling for predicting head vibration based on driving seating conditions: towards adaptive seating systems. Eng. Appl. Artif. Intell. 145, 110174. https://doi.org/10.1016/j.engappai.2025.110174.

Singh, A., Nawayseh, N., Samuel, S., Dhabi, Y.K., Singh, H., 2023b. Real-time vibration monitoring and analysis of agricultural tractor drivers using an IoT-based system. J. Field Robot. 40, 1723–1738. https://doi.org/10.1002/rob.22206.

Singh, A., Nawayseh, N., Singh, H., Dhabi, Y.K., Samuel, S., 2023c. Internet of agriculture: analyzing and predicting tractor ride comfort through supervised machine learning. Eng. Appl. Artif. Intell. 125, 106720. https://doi.org/10.1016/j.engappai.2023.106720.

Singh, A., Nawayseh, N., Singh, H., Samuel, S., Prakash, C., Singh, R., Kumar, Y., Singh, M., Chhuneja, N.K., 2022. Modelling and optimization of tractor ride conditions under water tanker operation. Theor. Issues Ergon. Sci. 23, 453–474. https://doi.org/10.1080/1463922X.2021.1981481.

Singh, A., Nawayseh, N., Singh, L.P., Singh, S., Singh, H., 2019. Investigation of compressive stress on lumbar spine due to whole body vibration exposure in rotary tillage operation. Int. J. Automot. Mech. Eng. 16, 6684–6696. https://doi.org/10.15282/ijame.16.2.2019.16.0503.

Singh, A., Nawayseh, N., Singh, L.P., Singh, S., Singh, H., 2018a. Whole body vibration exposure during rotary soil tillage operation:: the relative importance of tractor velocity, draft and soil tillage depth. Int. J. Automot. Mech. Eng. 15, 5927–5940. https://doi.org/10.15282/ijame.15.4.2018.15.0452.

Singh, A., Singh, L.P., Singh, S., Singh, H., Prakash, C., 2018b. Investigation of occupational whole-body vibration exposure among Indian tractor drivers. Int. J. Hum. Factors Ergon. 5, 151–165. https://doi.org/10.1504/IJHFE.2018.092240.

Tiemessen, I.J., Hulshof, C.T.J., Frings-Dresen, M.H.W., 2007. An overview of strategies to reduce whole-body vibration exposure on drivers: a systematic review. Int. J. Ind. Ergon. 37, 245–256. https://doi.org/10.1016/j.ergon.2006.10.021.

Varoquaux, G., Raamana, P.R., Engemann, D.A., Hoyos-Idrobo, A., Schwartz, Y., Thirion, B., 2017. Assessing and tuning brain decoders: cross-validation, caveats, and guidelines. NeuroImage, Individual Subject Prediction 145, 166–179. https://doi.org/10.1016/j.neuroimage.2016.10.038.

Velmurugan, P., Kumaraswamidhas, L.A., Sankaranarayanasamy, K., 2012. Influence of road surfaces on whole body vibration for suspended cabin tractor semitrailer drivers. J. Low Freq. Noise Vib. Act. Control 31, 75–84. https://doi.org/10.1260/0263-0923.31.2.75.

Wahlström, J., Burström, L., Johnson, P.W., Nilsson, T., Järvholm, B., 2018. Exposure to whole-body vibration and hospitalization due to lumbar disc herniation. Int. Arch. Occup. Environ. Health 91, 689–694. https://doi.org/10.1007/s00420-018-1316-5.

Yan, B., Pei, Y., Shuai, Z., Yang, Z., Jianhua, C., 2019. Research on classification model of natural driving scenario based on LightGBM. In: 2019 IEEE 19th International Conference on Communication Technology (ICCT). Presented at the 2019 IEEE 19th International Conference on Communication Technology. ICCT), pp. 1688–1693. https://doi.org/10.1109/ICCT46805.2019.8947318.

Yang, Y., Lv, H., Chen, N., 2023. A survey on ensemble learning under the era of deep learning. Artif. Intell. Rev. 56, 5545–5589. https://doi.org/10.1007/s10462-022-10283-5.

Zafar, M.R., Khan, N., 2021. Deterministic local interpretable model-agnostic explanations for stable explainability. Machine Learning and Knowledge Extraction 3, 525–541. https://doi.org/10.3390/make3030027.

Zanatta, M., Amaral, F.G., Vidor, G., 2019. The role of whole-body vibration in back pain: a cross-sectional study with agricultural pilots. Int. J. Ind. Ergon. 74, 102872. https://doi.org/10.1016/j.ergon.2019.102872.

Zeng, X., Kociolek, A.M., Khan, M.I., Milosavljevic, S., Bath, B., Trask, C., 2017. Whole body vibration exposure patterns in Canadian prairie farmers. Ergonomics 60, 1064–1073. https://doi.org/10.1080/00140139.2016.1252859.

Zhang, C., Guo, L.-X., 2023. Analysis of lumbar spine injury with different back inclinations under whole-body vibration: a finite element study based on whole human body models. Int. J. Ind. Ergon. 95, 103447. https://doi.org/10.1016/j.ergon.2023.103447.

Zhang, C., Meng, X., Anderson, D.E., Wang, W., Tao, X., Cheng, B., 2019. Effects of stretch reflex on back muscle response during sinusoidal whole body vibration in sitting posture: a model study. Int. J. Ind. Ergon. 71, 103–110. https://doi.org/10.1016/j.ergon.2019.02.005.

Zhang, X., Song, X., Wang, X., Yu, P., Qiu, Y., Miao, Y., 2024. Predicting the seat transmissibility of a seat-occupant system exposed to the whole-body vibration with combined artificial neural network and genetic algorithm. Int. J. Ind. Ergon. 103, 103627. https://doi.org/10.1016/j.ergon.2024.103627.

Zhao, X., Du, Yuefeng, Yang, Lichao, Mao, Enrong, Guo, Dafang, Zhu, Z., 2024. Effects of road type and IVIS task type on driver behavior and driving performance in agricultural tractors. Int. J. Hum. Comput. Interact. 40, 3159–3172. https://doi.org/10.1080/10447318.2023.2183309.

Zheng, Y., Wang, Y., Liu, J., Jiang, H., Yue, Q., 2021. Knee joint vibration signal classification algorithm based on machine learning. Neural Comput. Appl. 33, 985–995. https://doi.org/10.1007/s00521-020-05370-z.

Zhou, W., Yan, Z., Zhang, L., 2024. A comparative study of 11 non-linear regression models highlighting autoencoder, DBN, and SVR, enhanced by SHAP importance analysis in soybean branching prediction. Sci. Rep. 14, 5905. https://doi.org/10.1038/s41598-024-55243-x.

Zian, S., Kareem, S.A., Varathan, K.D., 2021. An empirical evaluation of stacked ensembles with different meta-learners in imbalanced classification. IEEE Access 9, 87434–87452. https://doi.org/10.1109/ACCESS.2021.3088414.