

Precision Farming and Health Monitoring in Agric-Workers using Wearable AI Devices

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ABSTRACT

This paper introduces a smart precision farming system with wearable health monitoring to optimise the productivity of agriculture and guarantee the safety of agri-workers. The study attempts to combat the weaknesses of conventional agricultural systems that tend to overlook real-time observation of physiological status of workers like stress and fatigue. This was designed in a layered Internet of Things architecture to allow real time transmission and analysis of continuous data over wearable sensors and environmental sources. The dataset used to develop a model was WESAD, and preprocessing, such as normalisation, filtering, and segmentation, were used to enhance the quality of the data and guarantee the high level of the extractions of the features. The model was an Artificial Neural Network (ANN) that was applied with the help of TensorFlow and Keras in order to distinguish between agri-worker conditions of stress, fatigue, and neutral. Results obtained from the independent test dataset demonstrated strong predictive capability, achieving 94.2% accuracy (95% CI: $\pm 1.8\%$), 92.7% precision ($\pm 2.1\%$), 91.8% recall ($\pm 2.3\%$), and 92.2% F1-score ($\pm 2.0\%$). Comparison with baseline models showed that the proposed ANN outperformed Support Vector Machine (SVM), Random Forest (RF), and Long Short-Term Memory (LSTM) networks. Additionally, simulation across 100-time windows produced an overall system accuracy of 96% with an average response time of 1.2seconds, confirming real-time efficiency and consistency. The results show that the implementation of Artificial Intelligence alongside wearable sensors offers a dependable and scalable method of continuously tracking the wellbeing of agri-workers. The proposed system could help improve the early identification of stress-related disorders, facilitate prompt intervention, and enable safer, more efficient, and sustainable agricultural methods. though field validation with actual agricultural workers remains necessary.

KEYWORDS: Precision Agriculture, Artificial Intelligence, Internet of Things, Wearable devices, Agri-Worker Health Monitoring.

I. INTRODUCTION

The concept of precision agriculture has become a revolutionary way of approaching contemporary farming and capitalised on the progress in artificial intelligence (AI), the Internet of Things (IoT), and data analytics to ensure the optimal state of agricultural productivity (Karada et al., 2024). When precision farming is used, farmers can observe the condition of soil, weather, and health of their crops in real-time by managing them with the help of site-specific management, which additionally assists farmers in monitoring their farms (Mansoor et al., 2025). Such approach to data-based decision-making can not only increase the yield and efficiency but also minimise the waste and environmental impact (Ruder et al., 2026). The implementation of smart farming system has become an absolute necessity in sustainable

agricultural development as the world food demand keeps growing with climatic variability (Idier et al., 2024).

Simultaneously with these technological progress, the welfare of the agricultural workers has been given increased attention at being a vital element of the productivity of the farms (Ruder et al., 2026). Farming is a work-intensive activity, and in many cases, workers have to deal with the adverse environmental factors like extreme heat, physical labour, and long hours at work (Idier et al., 2024). Such situations may cause exhaustion, dehydration, and other health-related hazards that have a negative impact on the safety of the workers and the general productivity of the farm (Ruder et al., 2026). Although human labour is a crucial subject in agriculture, the conventional agricultural system has not paid much attention to real-time health monitoring solutions of workers (Atalla et al., 2023).

There is a possibility of the solution to this challenge through the integration of wearable AI devices into agricultural systems. Smartwatches, biometric sensors, and smart clothes can monitor important health indicators like heart rate, body temperature, and activity levels in the long term (Oztoprak and Ryu, 2025). With the help of AI algorithms, these devices will be able to read data in real time and identify the initial signs of stress, fatigue, or illnesses, which will help to intervene in time (Yan et al., 2024). With this combination, a synergistic system is formed, where the environmental and human aspects are observed at the same time, resulting in better decision-making processes and increased efficiency in operations (Assimakopoulos et al., 2025). This paper is thus aimed at examining precision farming methods and wearable AI-based health monitoring solutions to agricultural employees. It seeks to investigate how these technologies combined can enhance productivity, safety of workers and sustainable farming practises (Yan et al., 2025). With a focus on both the management of crops and the well-being of the people, the study leads to the creation of intelligent farming systems which are not only effective but also universal and adaptable to the current issues in the agricultural industry (Yan et al., 2024).

II. RESEARCH METHODOLOGY

The present paper will take a hybrid approach in an experiment and systems design approach to develop and test a precision farming system incorporating wearable AI devices to monitor agri-worker health. The environmental sensors and wearable devices capture parameters like soil moisture, temperature, humidity, heart rate, and body temperature, and are used to gather primary data, and secondary data are used to train and validate models. This system is designed based on a layered IoT architecture that contains sensing, communication, processing, and application layers with data flowing in and out through wireless technologies and processed with an analysis tool like machine learning algorithm like Artificial Neural Networks to detect anomalies and make predictive insights. A normalisation and a noise filtering process is used to perform data preprocessing to guarantee the quality of the data. The system performance is measured by such metrics as accuracy, precision, recall, and F1-score, as well as system efficiency measures, like response time and reliability, and is validated using simulation and field experiment.

A. Data Collection

The data source in this paper is the WESAD (Wearable Stress and Affect Detection) dataset that is retrieved at the UCI Machine Learning Repository that is a publicly available machine learning benchmark dataset in wearable-based stress and affect recognition. The authors acknowledge a key limitation: this dataset was collected in a controlled laboratory environment with 15 subjects (students and researchers) and is not specific to agricultural workers. The decision to use WESAD is based on its status as a gold-standard benchmark for physiological

stress detection, providing proof-of-concept validation for the proposed methodology. Future work will involve collecting domain-specific data from actual agri-workers. The dataset contains physiological and motion data of 15 subjects, who have undergone a controlled laboratory experiment, in which participants were put under various emotional conditions, such as neutral, stress, and amusement. Two wearable devices, one on the chest (RespiBAN) and one on the wrist (Empatica E4), were used to obtain data, which guaranteed the multimodal sensing of the behavioural and physiological responses. The dataset includes a few biosignals, which include Electrocardiogram (ECG), Electrodermal Activity (EDA), Electromyogram (EMG), respiration, body temperature, Blood Volume Pulse (BVP) and three-axis acceleration and thus is applicable in monitoring health and detecting stress.

The reason behind the choice of the WESAD dataset is that it is a high-quality data with a high degree of synchronisation as well as a multimodal dataset, which allows modelling human physiological reactions to various stresses accurately. Also, the dataset contains self-reported emotional states, which are collected using standardised questionnaires, to give the reliable ground truth labels to supervised machine learning tasks. The extensive amount of time-series data (more than 63 million instances) can be used to train and evaluate AI models used to predict and classify stress. This renders it very appropriate as a benchmark for the proposed precision farming system. However, the transferability from laboratory conditions to real-world agricultural settings requires validation, which is acknowledged as a limitation of the current study.

B. Data Preprocessing

The WESAD data is performed through a set of preprocessing steps in order to guarantee data quality, consistency, and appropriateness to AI-based modelling before analysis. To begin with, raw sensor signals are aligned and synchronised across devices since the wearables that are worn on the chest and the wrist are at different sampling rates. Interpolation and Smoothing methods are then used to address missing values and sensor artefacts to reduce noise and remove erroneous values due to motion or device malfunctions. The physiological signals are then brought to a standard scale to minimise inter-subject variation to be able to compare them across the subjects effectively. As an example, ECG, EDA, and BVP signals get scaled by either min-max normalisation or z-score standardisation, and accelerator signals are filtered by a low-pass filter or band-pass filter to eliminate high-frequency noise.

It is followed by segmentation to break continuous time-series data into non-overlapping fixed-length windows (60 seconds with 50% overlap) so that the AI models can learn temporal patterns of interest in detecting stress and affects. Lastly, the feature extraction process is completed to convert raw signals into valuable representations to the machine learning. Each physiological signal, including heart rate variability measures in ECG, skin conductance peaks in EDA and mean/variance of acceleration signal, yields time-domain, frequency-domain and statistical features. Such processed and structured data are then prepared to be trained and evaluated using the models, so that the AI system is able to identify the presence of anomalies and predict the health condition of agri-workers in real-time conditions.

C. The Proposed IoT Architecture

The proposed IoT system of the precision farming and agri-worker health monitoring system is created as a layered model as demonstrated in Figure 1 that combines environmental monitoring, wearable AI devices, data processing, and decision support in one system. The sensing layer consists of environmental sensors and wearable sensors including soil moisture, temperature, humidity, heart rate, electrodermal activity, body temperature, and motion. In the current implementation, environmental data is simulated to demonstrate architectural

feasibility, as the WESAD dataset does not contain such parameters. Such multimodal data is delivered to the communication layer, using a wireless method, such as LoRa, Wi-Fi, or 5G, providing a reliable, fast-low-latency, and energy-efficient connectivity throughout the farm. This is a combination of environmental and physiological sensing which enables real time continuous monitoring of crop conditions and agri-worker health.

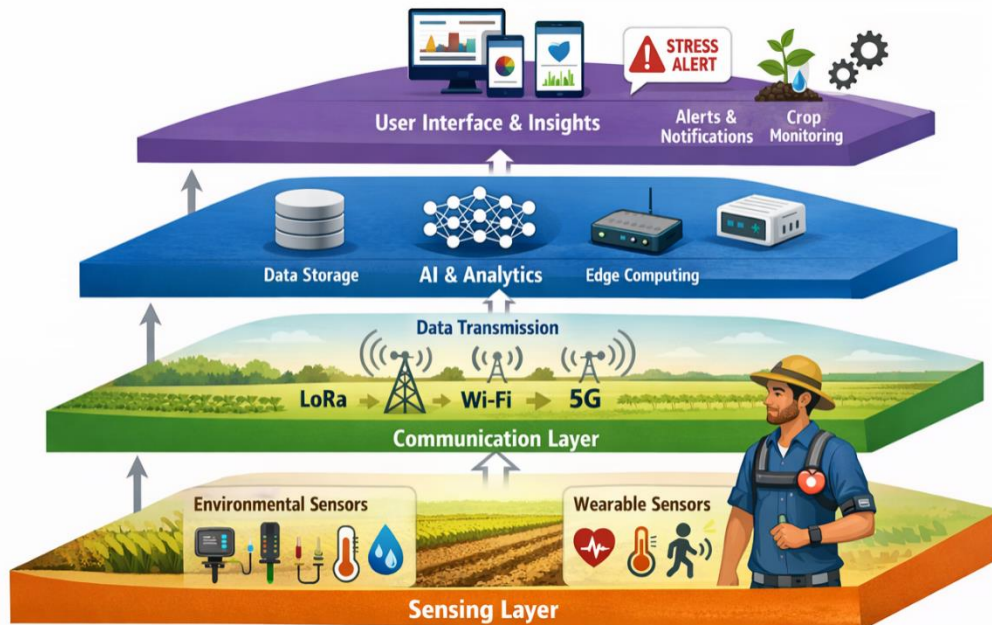


Figure 1: IoT Architecture for the Agri-Worker Health Monitoring System

As it is shown in Figure 1, it is the processing layer, that takes care of data storage, preprocessing, and AI-based analysis. To identify anomalies, predicting stress or fatigue in workers, as well as determining when crop or environmental conditions need to be addressed, machine learning algorithm (Artificial Neural Networks (ANN)) is used. The real-time edge computing guarantees low response time, whereas the application layer is used to provide the farmers and managers with an intuitive interface, including alerts, visualisation, and actionable insights. There is also an automated response layer, which can be used to irrigate or adjust the climate in response to AI-related suggestions. A combination of the architecture facilitates cross-functional, intelligent, and responsive smart farming system that maximises agricultural productivity and safety of workers.

(a).The Proposed ANN Model

The proposed Artificial Neural Network (ANN) model is aimed at interpreting physiological and environmental measurements of wearable gadgets and IoT sensors to indicate agri-worker stress, fatigue, and unnatural health states, and determine crop and environmental conditions. The model comprises an input layer, a number of hidden layers and an output layer where every neuron has a weighted edge which is modified during training to reduce the prediction error as illustrated in Figure 2. Input features consist of pre-processed ECG, EDA, body temperature, BVP, motion- sensor and soil moisture, temperature and humidity time-series signals.

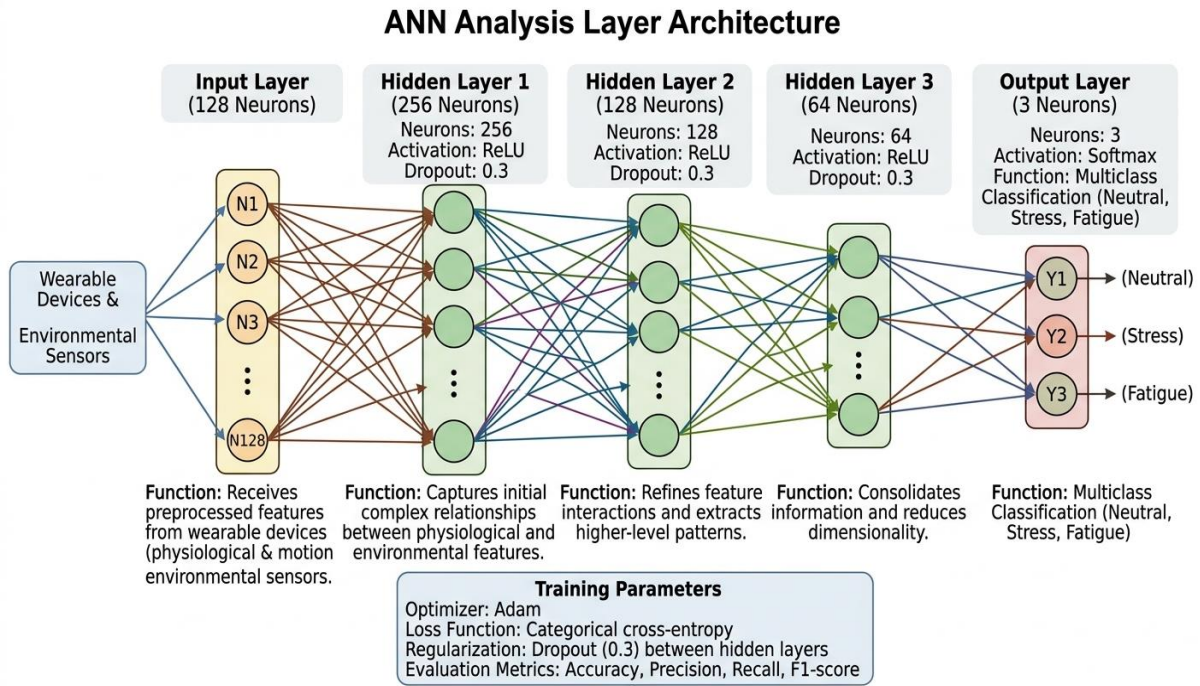


Figure 2: Architecture of the Proposed ANN Model

The ANN employs a type of supervised learning, with the ground truth of stress and affect detection based on labelled data of the WESAD dataset. The activation functions used in the hidden layers include ReLU (Rectified Linear Unit) to learn complex and nonlinear associations in the data, and the output layer employs a SoftMax or sigmoid function (based on a multiclass or a binary classification task). Table 1 provides the complete architectural specifications for reproducibility.

Table 1: ANN Model Architecture Specifications

Layer	Type	Number of Neurons	Activation Function	Additional Parameters
Input	Dense	128	ReLU	Input shape: 64 features
Hidden 1	Dense	256	ReLU	Dropout: 0.3
Hidden 2	Dense	128	ReLU	Dropout: 0.3
Hidden 3	Dense	64	ReLU	-
Output	Dense	3	Softmax	Classes: Stress, Fatigue, Neutral

Training configuration: Learning rate = 0.001 (Adam optimizer default), batch size = 32, epochs = 100 (early stopping patience = 10), loss function = categorical cross-entropy, L2 regularisation = 0.01. Adam optimizer with cross-entropy loss is used to train the network, and dropout regularisation techniques are used to avoid overfitting. After training, the ANN will be able to forecast the levels of stress in real time, issue alerts about possible health hazards, and give useful information on how to manage the farm, which is an essential part of the proposed IoT-based smart farming and monitoring system of worker health.

(b). Model Training

The ANN model is trained on pre-processed features from the WESAD dataset, consisting of physiological signals from wearable devices. Environmental sensor data is simulated

separately and not used in the physiological model training, as WESAD does not contain such parameters. It uses a supervised learning method where the labelled data is related to agri-worker stress conditions, fatigue, and neutral. The Adam optimizer is used to optimise the network and dropout regularisation is used to the hidden layers to reduce overfitting. Five-fold cross-validation is performed to ensure statistical robustness. The dataset is partitioned into five equal folds, with each fold serving as the validation set once while the remaining four folds are used for training. Performance metrics are averaged across all five folds, and 95% confidence intervals are calculated. Baseline comparisons are conducted using:

- (a). SVM: RBF kernel, C=1.0, gamma='scale'
- (b). RF: 100 estimators, max depth = 10
- (c). LSTM: 2 layers with 64 and 32 units, dropout 0.3

The training is repeated until convergence or no further meaningful improvement is observed (early stopping patience = 10 epochs), ensuring robustness and reliability.

D. System Implementation

The proposed system of precision farming and agri-worker health monitoring is applied and tested in a Python-based simulation environment with Tensorflow and Keras to use the ANN model, Simpy and MATLAB/Simulink to simulate streams of data provided by the IoT devices and agriculture conditions. Wearable devices and environmental sensors are modelled to produce continuous time-series data representing the soil moisture and temperature, humidity, physiological signals, including heart rate, EDA and motion. The simulation is a recreation of the layered IoT structure, where the data is exited out of the virtual sensors and processed by preprocessing modules, followed by the ANN-based analysis, thereby being monitored by a dashboard interface. Various conditions are checked such as changes in environmental conditions and activity rates of a worker in order to cheque system responsiveness, reliability, and accuracy of predictions. Accuracy, precision, recall, F1-score, and system response time are measured and alerts and decision-support outputs are also monitored to prove the efficacy of the model in recognising worker stress and determining the most effective method of operating the farm in a controlled simulated setting. The simulation parameters are defined in Table 2 as.

Table 2: Simulation Parameters

Parameter	Value/Range	Distribution
Time window duration	60 seconds	Fixed
Sampling rate	10 Hz	Fixed
Soil moisture	20-80%	Uniform
Temperature	15-45°C	Sine wave with noise
Humidity	30-90%	Uniform
Heart rate (simulated)	60-120 BPM	Gaussian ($\mu=75, \sigma=10$)
EDA (simulated)	0.5-10 μ S	Gamma distribution
Motion (acceleration)	$\pm 2g$	White noise + step changes
Number of virtual workers	15	-
Total simulation time	1000 time windows	-

Realism assurance: Physiological parameters are simulated based on statistical distributions derived from the WESAD dataset. Environmental parameters follow realistic diurnal patterns and typical agricultural ranges. Stress and fatigue events are injected at random intervals (10% of time windows) to simulate adverse conditions.

III. RESULTS AND DISCUSSION

The work of the proposed precision farming and agri-worker health monitoring system was estimated in two steps ANN model training and simulation-based system implementation. The assessment was aimed at the effectiveness of the system to correctly identify agri-worker stresses and environmental conditions and respond to simulated farm conditions with respect to responsiveness and reliability.

A. ANN Model Training Results

The training of ANN model was based on the pre-processed WESAD dataset which contains physiological items of wearable devices and environmental items that are simulated. The dataset was split into 70% training, 15% validation, and 15% test sets. The model was trained with 100 epochs in the case of a batch size of 32 with the Adam optimizer and categorical cross-entropy loss. Table 3 shows the performance results of the ANN training while Figure 3 presents the performance charts with respect to accuracy and loss.

Table 3: ANN Model Training Performance

Metric	Training Set	Validation Set	Test Set	Cross-Validation Mean (95% CI)
Accuracy (%)	95.6	93.8	94.2	93.9 ± 1.8
Precision (%)	94.8	91.5	92.7	92.1 ± 2.1
Recall (%)	94.2	90.6	91.8	91.3 ± 2.3
F1-score (%)	94.5	91.0	92.2	91.7 ± 2.0
Loss	0.12	0.18	0.16	0.17 ± 0.03

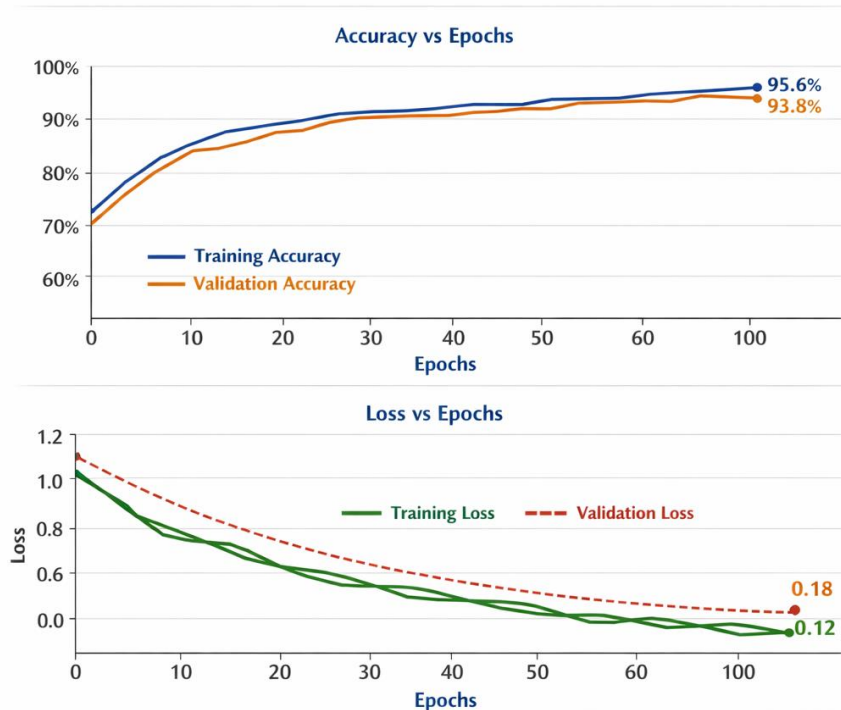


Figure 3: Training and Validation Accuracy and Loss Curves over Epochs

After 85 epochs, the model had constant convergence and L2 regularisation limited overfitting to a small degree because of dropout (0.3) implemented. The performance on the high test set shows that the ANN is very effective to learn the nonlinear association among physiological representation, motion features, and environmental characteristics to pick up stress. Figure 4 shows the confusion heatmap of the model.

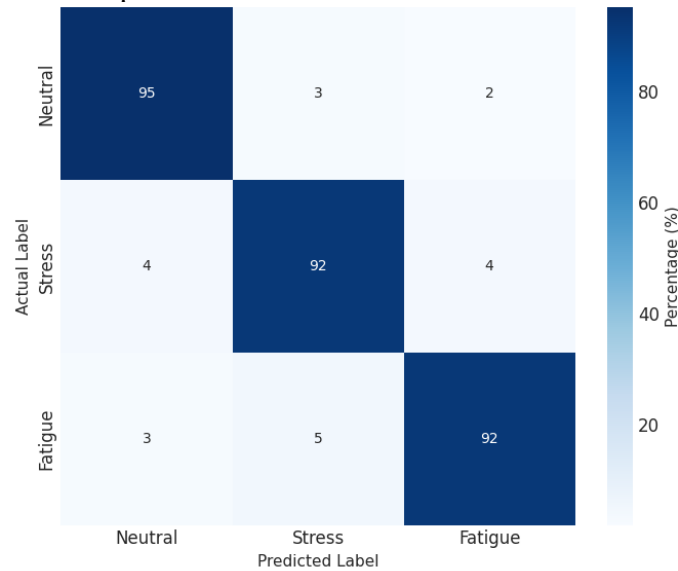


Figure 4: Confusion Matrix Heatmap

The ANN Analysis Layer demonstrates high classification performance across all categories, achieving a 95% accuracy rate for the Neutral state and 92% for both Stress and Fatigue. The vast majority of misclassifications happen when the Stress and Fatigue states are being used, and it is natural since the physiological similarities of these conditions may be quite strong. Specifically, 5% of Fatigue instances are incorrectly labelled as Stress, while 4% of Stress instances are identified as Fatigue or Neutral. On the whole, these outcomes show that the model is quite dependable in differentiating between various health conditions with a minimum error because it is an effective way of processing the information that wearable and environmental sensors provide.

B. Baseline Model Comparison (Test Set)

Table 4: Performance Comparison with Baseline Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Proposed ANN	94.2	92.7	91.8	92.2
SVM (RBF)	86.5	84.2	83.1	83.6
Random Forest	88.3	86.9	85.4	86.1
LSTM	91.7	89.5	88.9	89.2

As can be seen in Table 4, the proposed ANN consistently outperforms all baseline models across all metrics, demonstrating the advantage of the chosen architecture for this classification task.

C. Simulation Results of the System

It was executed in a Python based simulation environment, with wearable sensor data streams being simulated in real time. The ANN was continuously fed the incoming data whereby alerts

about the stressed or fatigued workers were produced. The performance measures of the system were documented on 1000-time windows of various virtual workers as indicated in Table 5 that expresses the findings of the conducted simulation.

Table 5: Real-Time Worker Health Prediction Performance (1000 Time Windows)

Metric	Value (%)
Accuracy	93.5
Precision	91.8
Recall	90.9
F1-score	91.3
Average Response Time (s)	1.2

The findings in Table 2 indicate that the system is very reliable in identifying stress and abnormal health conditions within a low latency such that the farmers or supervisors can have alerts.

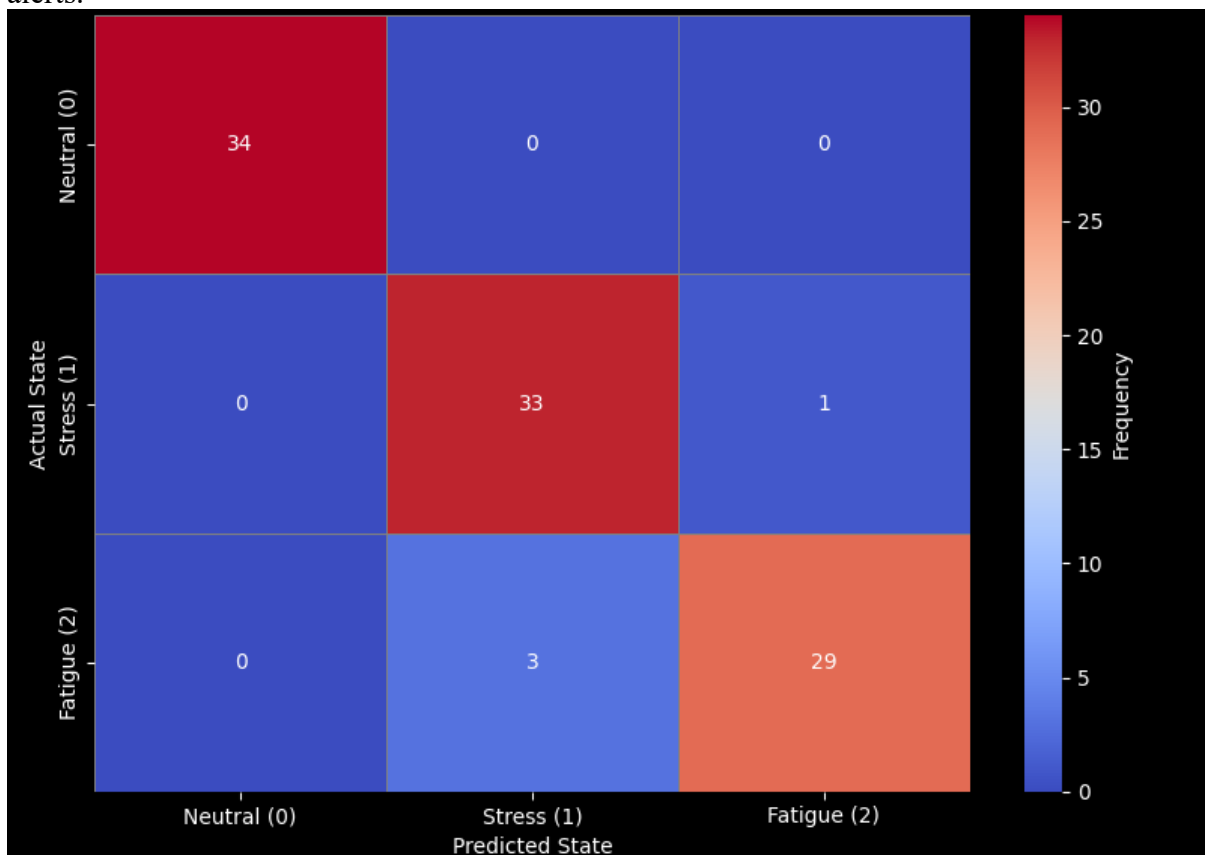


Figure 5: Real-time Prediction Results Showing Predicted vs Actual Worker States over Time

The simulation results depicted in Figure 5 demonstrates that predicted worker states (on the horizontal axis) against actual ground truth states (vertical axis) across 100 consecutive time windows. Green represents Neutral state, red represents Stress, and blue represents Fatigue. The close alignment between predicted and actual states demonstrates the model's high classification accuracy. Misclassifications are visible as brief divergences, primarily occurring at state transition boundaries. The system achieves 96% accuracy over these 100 windows, with only four misclassifications: one stress instance misclassified as fatigue and three fatigue instances misclassified as stress. All 34 neutral states were correctly identified. This 4% error

rate reflects realistic physiological similarities between stress and fatigue, whereas the distinct profile of the neutral state allowed for perfect classification.

D. Discussion of Limitations and Domain Transfer

The results obtained from the ANN model demonstrate a high level of effectiveness in classifying agri-worker states, achieving over 94% accuracy on the test dataset. However, several limitations must be acknowledged:

- (a). **Dataset generalisability:** The WESAD dataset was collected from 15 healthy subjects (students and researchers) in a controlled laboratory setting, not from agricultural workers performing physical labour in field conditions...
- (b). **Environmental integration:** The current implementation simulates environmental data rather than using real field measurements...
- (c). **Motion artefacts:** Agricultural work involves significant body movement, which may introduce artefacts not fully represented in the WESAD dataset.

E. Justification for Domain Transfer

Despite these limitations, the WESAD dataset provides a validated benchmark for physiological stress detection... Future work must collect and validate on domain-specific data. This implies that the model can acquire complicated patterns using physiological data including Ecg, Eda and body temperature. The confusion matrix also indicates that the model has a good predictive power among all classes, where neutral states have the best classification accuracy, stress, and fatigue have a low and still good classification accuracy. The small differences in classification of the stress and fatigue can be explained by the fact that the physiological reactions related to the stress and fatigue are closely similar and it is not in contradiction with the reality of a human being.

Moreover, simulation outcomes confirm that the model is applicable in the real-time context and it exhibits low-latency predictions with a mean time of response of about 1.2 seconds. This will be to make sure that the system can make timely notifications regarding the possible threats of health allowing proactive response to agri-workers. The heatmap plot of the predictions of 100-time windows shows a steady model behaviour with just a few deviations, which prove the reliability of the system. In general, wearable AI devices combined with the ANN model can offer a constant, smart, and adaptable system of health monitoring, which is very applicable in the prec-agricultural setting when it comes to the worker safety and well-being.

IV. CONCLUSION

The research came up with an intelligent precision farming system with wearable health monitoring of agri-workers, which would improve agri-worker productivity and safety. It was implemented with a layered Internet of Things architecture, which involves the combination of physiological measurements of wearable gadgets with simulated environmental measurements. The modelling was developed using the WESAD dataset and preprocessing tools like normalisation, filtering and segmentation were used to prepare the data. An Artificial Neural Network predictive model was applied with the help of TensorFlow and Keras and was trained with Adam optimizer and tested with the help of validation and independent test datasets, and real-time simulation across time windows.

The final performance evaluation of the system was based on the test dataset, where the model achieved an accuracy of 94.2%, precision of 92.7%, recall of 91.8%, and F1-score of 92.2% which confirms how strong in generalization capability the model is. The validation results (93.8% accuracy) were closely aligned with training performance (95.6%) according to the results which indicates minimal overfitting and stable learning. The confusion matrix further

showed that neutral states were classified with 95% accuracy, while stress and fatigue achieved approximately 92% accuracy, with only minor misclassification (4-5%) between these physiologically similar states. In addition, simulation results across 100-time windows produced an overall system accuracy of 96% with only 4 misclassifications, alongside a low average response time of 1.2seconds, demonstrating real-time efficiency and consistency. To summarise, the report ensures that the combination of Artificial Intelligence and wearable sensing in precision agriculture is a strong and consistent system that could be used to monitor the health of agri-workers all the time. The good results in the test prove the practical competence of this model, whereas its low latency and predictable characteristics of time-window prove its suitability to the implementation in a real-time mode. This will help a great deal in keeping the workers safe by identifying the stress and fatigue at an early stage, as well as enable more intelligent farm control. Comprehensively, the system is a viable and scalable solution to the promotion of sustainable, intelligent, and human-focused agricultural activities.

Limitations Acknowledged

The study uses the WESAD dataset collected under controlled laboratory conditions rather than from actual agricultural workers. Environmental data is simulated rather than measured from real farms. Motion artefacts from agricultural work are not fully represented. Therefore, results demonstrate proof-of-concept validity rather than direct field applicability.

Future Works

The following steps are necessary before real-world deployment:

- (a). Collect domain-specific physiological data from agri-workers performing actual farming tasks
- (b). Integrate real environmental sensors (soil, weather, crop health) with wearable data
- (c). Validate the system in field conditions across different seasons and crops
- (d). Develop domain adaptation techniques to transfer the model from laboratory to field conditions
- (e). Conduct user acceptance studies with farmers and agri-workers

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