Industrial Internet of Things for Assembly Line Worker's Work Fatigue Recognition

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Abstract: The fourth industrial revolution or Industry 4.0 is based on the Internet of Things (IoT) and other intelligent technologies. IoT is mature enough to make seamless real-time communication between data-grasping sensors and intelligent machines. Recognition and prevention of workers' work fatigue remain challenging for manufacturing industries. The objective of this research is to develop an IoT-based worker's work fatigue recognition system to recognize the real-time fatigue status of assembly line workers. A learning-based knowledge model is prepared from the historical worker's work fatigue status to classify the worker's work fatigue status (as 'Yes' or 'No') using the real-time monitoring system. Where a sensor-connected IoT framework is adopted for monitoring the real-time state of an assembly worker. Finally, an intelligent system is proposed to recognize the real-time worker's fatigue status from the IoT real-time monitored data using the learning-based worker's work fatigue recognition model. A use-case illustration is given to demonstrate the research scope for a manual assembly line.

1 INTRODUCTION

Workers' work stress or work fatigue is one of the leading contributors to assembly line work errors, which could become a bottleneck to work productivity or product quality. Assigning a task to an operator for an extended period can lead to worker work stress or work fatigue, resulting in an efficiency loss or disinclination of efforts or Musculoskeletal disorders (MSDs) (Grandjean, 1979). Work-related musculoskeletal disorders (WMSD) are caused by the poor work environment or Ergonomics of the workplace (Govaerts et al., 2021). Neck, shoulder, and back-related problems are widely seen MSDs in manufacturing workers (Yang et al., 2023), causing 34% of annual work time loss and 7% loss of manufacturing productivity (Nur et al., 2014). Moreover, the objective of Industry 5.0 is to transform manufacturing companies from a technology-centred approach to human-centric, sustainable, and resilient manufacturing (Abdous et al., 2023). This research aims to develop an intelligent worker's fatigue status recognition system to identify the assembly line fatigued worker, which supports the assembly line manager or supervisor while finding and facilitating the assembly line fatigued workers.

Industry 4.0, or the Fourth Industrial Revolution, is providing a new direction to the manufacturing industries by the application of digital technologies. The Internet of Things (IoT) is a modern and fast-growing technology that has become a part of the realization of Industry 4.0. IoT is a real-time connecting link between the physical and digital entities (Manavalan & Jayakrishna, 2019). A typical IoT framework comprises sensors, edge gateways, and a middleware cloud platform deployed to enable real-time data. The Industrial Internet of Things (IIoT) refers to the use of IoT technologies in manufacturing or factory floor applications. IoT is an interconnection of many devices through an internet system capable of monitoring, collecting, exchanging, analyzing, and delivering data or information (Al-Turjman & Alturjman, 2018). IoT can be built with various "smart" sensors for

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intelligent monitoring and data extraction. The monitored data can be processed or mined with data analytics and machine learning techniques to make knowledge objects or models, eventually used for intelligent decision-making.

A learning mechanism makes a learning-based model, which makes a relation between monitoring factors and the effect. However, the learning can be either from sensing, historical experience, or a well-defined source of knowledge. A classification model can be developed through a learning process with historical experiences or data points. Clustering learning and classification learning are sequential steps to recognize the patterns. Where the historical experiences or data points are grouped into meaningful clusters or classes, the class labels can be used to build the classification mechanism (Cai et al., 2009). Historical fatigued worker status can be monitored. The monitored fatigued status data can be classified as 'Yes' and 'No' classes. Furthermore, a fatigued status classification model can be developed with the worker fatigue status classified data. The application of sensors, IoT, and classification learning to detect the real-time fatigue status of the assembly workers is the main research objective of this work.

2 LITERATURE REVIEW

Worker's work stress and Musculoskeletal disorders (MSDs) remain a considerable problem to the manufacturing industry around the world. Workers' work fatigue impairs work performance in alertness, emotional stability, and mental and physical ability (Sawatzky, 2017). (Sundstrup et al., 2020) have discussed some of the typical MSDs observed in industrial workers. Back or neck pains are the typical MSDs observed in industrial workers. Health issues such as memory or concentration loss, brain fog, increased risk of stroke, cardiovascular disease, hypertension, and decreased immunity are seen in fatigued workers (Sawatzky, 2017). (Sedighi Maman et al., 2020a) have attempted to recognize physical fatigue using wearable sensors and machine learning methods.

(Sadeghniiat-Haghighi & Yazdi, 2015) have presented a detailed review on workers' work stress or fatigue. Furthermore, they elaborated fatigue measurement techniques at the workplace regarding physical, mental, and environmental aspects. (Fardhosseini et al., 2020) used a three-axis accelerometer to recognize the physical fatigue of construction workers. (Ma et al., 2009) used electromyography and heart rate methods to measure muscular fatigue. (Baghdadi et al., 2019) used electroencephalography (EEG) to detect the mental fatigue of workers. (Charbonnier et al., 2016) used electromyography (EMG) to recognize localized muscle-related fatigue of workers. (Iskander et al., 2018) used optical sensors to detect sleepiness. (Halim et al., 2012) have done fatigue assessments for prolonged standing workers using surface electromyography (sEMG).

(Givi et al., 2015) and (Elmaraghy et al., 2008) discussed worker's work stress or fatigue-causing parameters, such as assembly task repetition, task complexity, task duration, task environment, worker work skill, workplace ergonomic design, assembly line speed, worker personality, working teams, coordination, management strategy towards the work, work distance, working space, worker motivation level, length of task cycle, work interruptions, Etc.

(Pabolu & Shrivastava, 2021) given learning-based fatigue classification function in terms of worker and workload attributes. (Usuga Cadavid et al., 2020) discussed learning methods widely using in the Industry 4.0 era. Association rules, K-Nearest Neighbors (k-NN), Bayesian networks, Naïve bayes models, linear regression models, polynomial regression, Gaussian process regression, Q-Learning, R- learning, decision trees, bagging, gradient boosting, random forest, ensemble learning, support vector machine, etc., are some of the techniques widely using in the industry 4.0 era. (Dogan & Birant, 2021) gave a detailed review of machine learning methods useful to resolve manufacturing challenges during the fourth industrial evolution. (Sedighi Maman et al., 2020b) have discussed three types of learning-based models to formulate the worker's stress behavior. Those are statistical models, classifiers, and ensemble models. (Pabolu et al., 2022) have proposed a prediction system using machine learning applications to predict the comfortable work-duration time of an assembly line worker by considering the worker, work, and work environment.

The application of intelligent systems in the predictive maintenance of industrial equipment by fault diagnosis and prognosis can be seen during the Industry 4.0 era (Li et al., 2017). (Vogl et al., 2019) have given a detailed review of diagnostic and prognostic capabilities and corresponding possibilities to make best practices in manufacturing. Furthermore, it is described that prognostics and health management can be done with intelligent decision-making using inference knowledge, which is made with real-time and historical state information

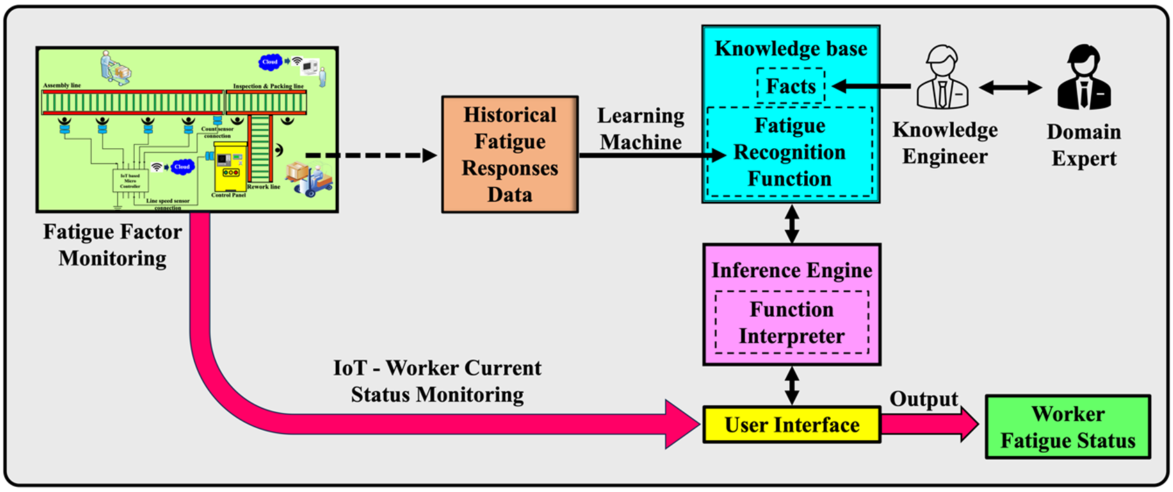


Figure 1: IoT-based intelligent fatigue recognition system.

of subsystems and components. The application of cyber tools to manage operator health using diagnostic and prognostic capabilities is the ongoing research trend during this decade. The potential requirement or research gap noticed during the literature study is to display or show the real-time fatigue status of all final assembly line workers using diagnostic and prognostic capabilities. The development of a wearable sensor-connected IoT-based intelligent work fatigue recognition system to recognize the real-time fatigue status of the assembly line workers is the contribution of this research to fill the research gap partially.

3 IOT-BASED WORKER'S FATIGUE STATUS RECOGNITION SYSTEM

An IoT-based intelligent fatigue recognition system is proposed to recognize workers' fatigue status. Figure 1 shows the proposed framework to recognize the assembly line fatigued worker. A set of sensors is to be placed on the assembly line worker to monitor the worker's fatigue status. Furthermore, the IoT framework transfers the fatigue factor's sensor data to the cloud. Then, an intelligent fatigue recognition system reads the worker's fatigue factor data and recognizes the worker's work fatigue status using a learning-based fatigue status recognition function. Details of worker fatigue status recognition function (*i.e.*, inference rule to invoke knowledge), IoT status monitoring, and intelligent fatigue status recognition are discussed in the following part of this section.

Worker Fatigue Status Recognition Function

The worker fatigue status recognition function is a function to recognize the fatigued status of an assembly worker from their current status. Equation 1 represents the worker fatigue status recognition function. The worker fatigue status recognition function is a function of the worker's age, sex, eye blink rate, heart rate, and active hand moment. Where eye blink rate is considered in blinks per minute, heart rate is considered as heart rate reserve in beats per minute, and active hand moment is in the form of acceleration (m/s^2).

Table 1: Description of indexes.

Index	Description
WFS	Worker Fatigue Status
a	Worker's age
s	Worker's sex
EBR	Eye Blink Rate
HRR	Heart Rate Reserve
DHR	Direct Heart Pulse Rate
RHR	Resting Heart Pulse Rate
HM	Hand Moment

$$\text{Worker Fatigue Status (WFS)} = f(a, s, EBR, HRR, HM) \quad (1)$$

$$HRR = \frac{(DHR - RHR)}{RHR} * 100 \quad (2)$$

$$HM = \sqrt{\left((A_x)^2 + \left(A_y\right)^2 + (A_z)^2\right)} \quad (3)$$

Equation 2 calculates heart rate reserve (HRR), which is a function of the direct heart pulse rate (DHR) in beats/min., and resting heart pulse rate

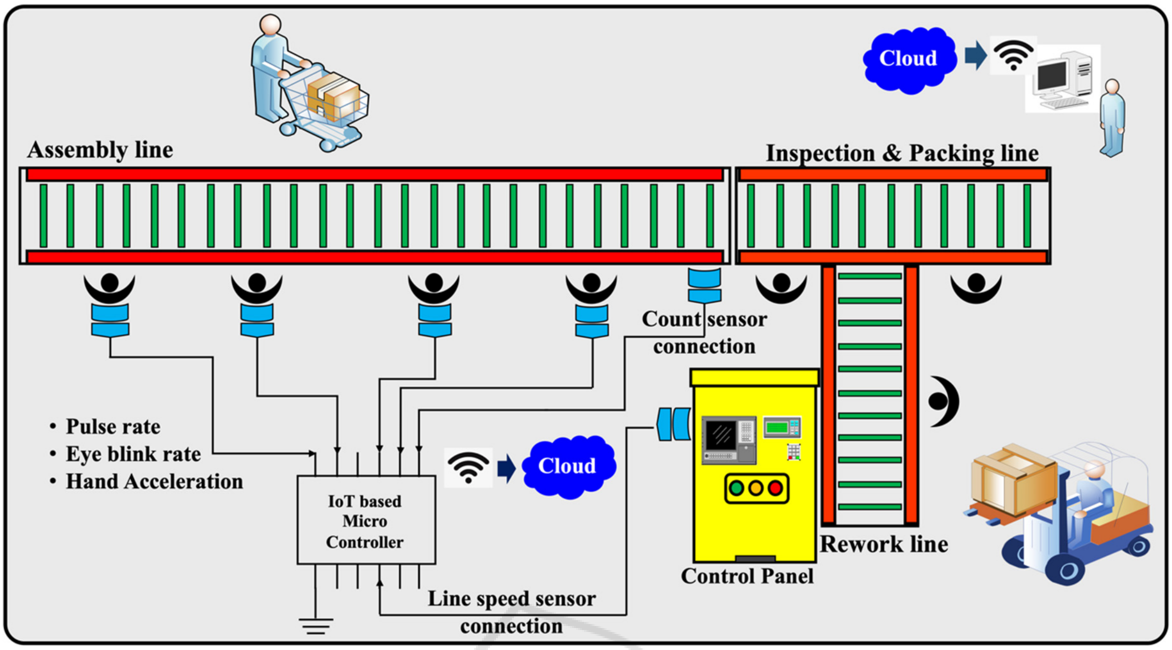


Figure 2: IoT based worker fatigue factor monitoring.

(RHR) of the corresponding worker. Equation 3 is to calculate the active hand moment, which is a vector product of hand acceleration components (*i.e.,* A_x, A_y, A_z) in m/s^2.

Table 2: Historical Fatigue Response Data.

a	*s*	*EBR*	*HRR*	*HM*	*Fatigue Status*
xx	x	xx	xx%	x.xx	Yes
xx	x	xx	xx%	x.xx	No

The worker fatigue status recognition function is a learning model learned from the historical worker fatigue status data. Table 2 shows the format of historical worker fatigue status data, will be given to the learning machine. A range of machine learning classification models are available in the literature as Logistic Regression, Polynomial SVM, Decision Tree, Random Forest, xgBoost, Naïve Bayes, k-Nearest Neighbour, Linear Discriminant Analysis, Quadratic Discriminant Analysis, Etc, (Wang, 2019). A suitable machine learning classification model can be used to make the worker fatigue status recognition function for the historical worker fatigue status data (*i.e.,* Table 2).

The machine learning model (*i.e.,* Worker fatigue status recognition function) acts as an inference rule, which will be stored in the knowledge base. Apart from the inference rule, the knowledge base also contains the facts about the assembly line workers, including details of the factory's assembly line workers list, corresponding age, sex, and resting heart pulse rate (*i.e.,* RHR).

IoT Status Monitoring

During the IoT status monitoring, a set of sensors, such as an eye blink sensor to measure the eye blink rate of the worker, a pulse sensor to measure direct heart pulse rate (*i.e.*, DHR), and an IMU sensor to measure hand acceleration must be placed on the assembly line worker. Furthermore, the sensors must be connected to the IoT controller. The IoT controller sends the worker's current status or sensor's monitored data to the cloud or server. The IoT monitoring framework is shown in Figure 2.

Intelligent Fatigue Recognition

The intelligent fatigue status recognition algorithm does the worker fatigue status recognition. Figure 3 shows the framework of an intelligent worker's fatigue status recognition algorithm. The algorithm takes the parameters of the worker fatigue status recognition function (*i.e.,* eq. 1) from the facts of the knowledge base and IoT-monitored data. Where the worker's age, sex, and RHR are from the facts of the knowledge base, and DHR, EBR, and HR values are from the IoT-monitored data. However, HRR can be calculated using Equation 2. An inference engine takes all parameters of the worker fatigue status recognition function (*i.e., a, s, HRR, EBR, HR*) and finds the worker's fatigue status using the worker fatigue status recognition function (*i.e.,* eq. 1).

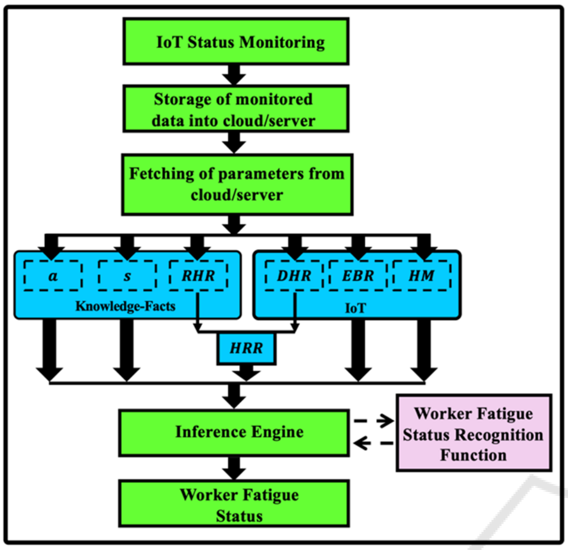


Figure 3: Intelligent Fatigue Status Recognition Algorithm.

4 USE-CASE ILLUSTRATION

Let the IoT monitored status of an assembly worker (*i.e.,* worker9) is Figure 4. However, facts of the respective worker are in Table 3. The objective is to find the fatigue status of the corresponding worker (*i.e.,* worker9).

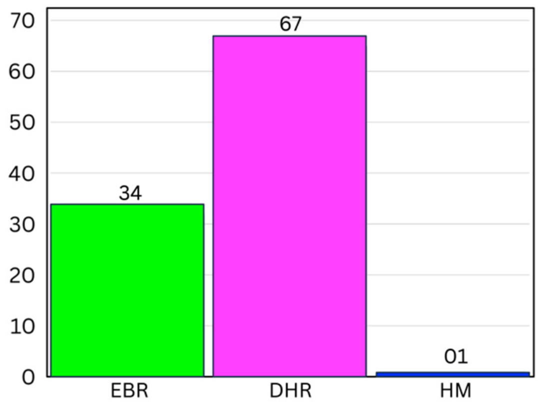


Figure 4: Worker9 IoT monitored status.

Table 3: Facts of worker9.

Worker Name	*a*	*s*	*RHR*
Worker9	36	F or (0)	54

Let the historical worker's fatigue response data is Table 4. Where '0' is considered for female workers and '1' is considered for male workers. Similarly, 'Y' represents the worker under fatigued conditions, and 'N' represents not fatigued. The data set (*i.e.,* Table 4) is prepared data (*i.e.,* not-real) exclusively prepared for illustration.

Equation 4 shows the linear fit for the historical worker's fatigue response data (*i.e.,* Table 4) at 80% of learning and 20% of the test data set with 10-fold crass validation. However, Figure 5 shows the accuracy of all learning models where the linear regression fit (*i.e.,* eq. 4) is considered as the worker's fatigue status recognition function for the use-case illustrative example.

Table 4: Historical worker's fatigue response data.

a	*s*	*EBR*	*HRR*	*HM*	*Fatigue Status*
22	0	23	10	2	N
35	0	32	22	3	Y
44	0	32	43	2	Y
53	0	25	35	2	Y
34	0	25	28	2	N
24	1	26	24	1	N
39	1	26	23	4	N
49	1	24	24	2	N
50	1	31	28	4	Y
39	1	27	31	2	Y
25	1	32	52	1	Y
22	0	23	10	2	N

$$WFS_{linear} = 1.282\,a - 23.659s + 5.722\,EBR + 1.278\,HRR + 1.117\,HM - 233.670 \quad (4)$$

Figure 6 shows the input to the learning-based worker's fatigue status recognition function (*i.e.*, eq. 4) to recognize the worker9's work-fatigue status, where HRR is calculated using equation 2.

Table 5: Predicted work-fatigue response for worker9.

a	*s*	*EBR*	*HRR*	*HM*	*Fatigue Status*
36	0	34	24	1	Y

Table 5 shows the predicted work-fatigue response by the worker's fatigue status recognition function (*i.e.,* eq. 4) for the worker9 based on the monitored IoT current status (*i.e.,* Figure 4). The worker's fatigue status recognition function is predicted as worker9 under fatigued condition.

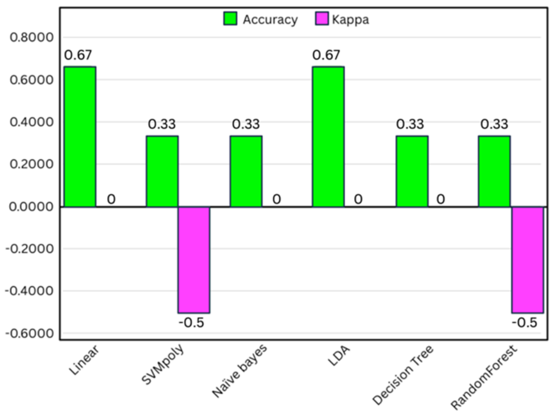


Figure 5: Accuracy of the learning models.

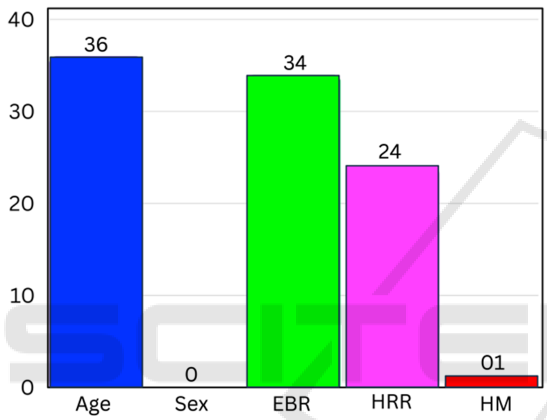
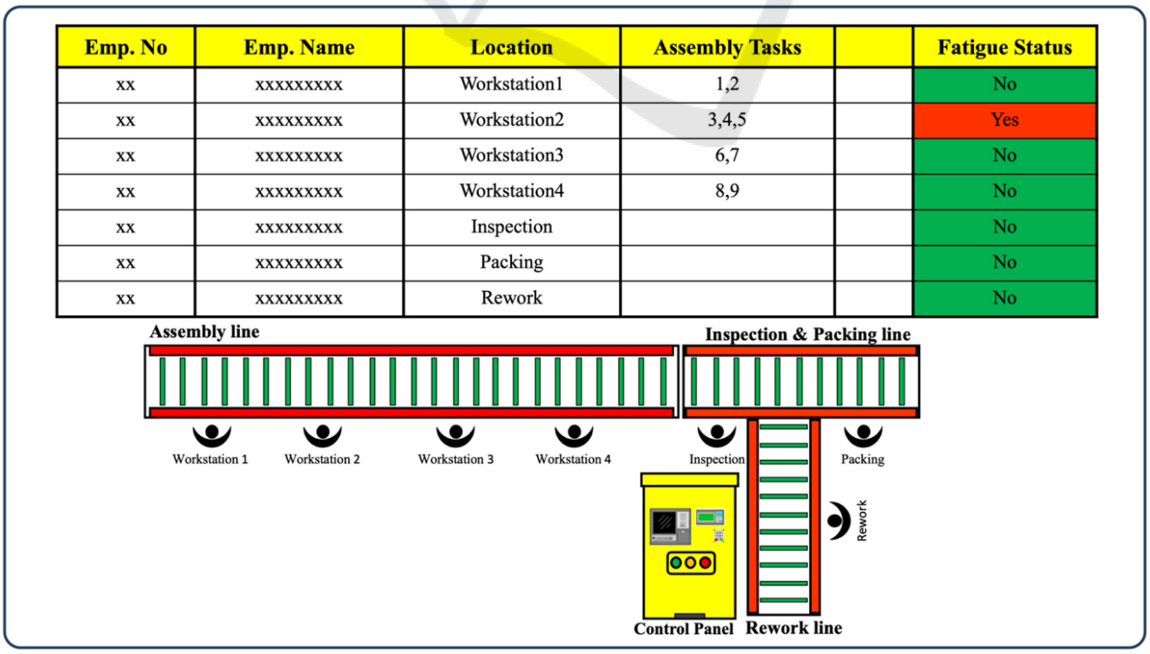


Figure 6: Input to the fatigue status recognition function.

5 DISCUSSION AND WORK IMPLICATION

An IoT-based intelligent fatigue recognition system is proposed for finding an assembly line fatigued worker. The proposed framework is helpful to an assembly line supervisor or manager while recognizing an assembly line fatigued worker and facilitation. Furthermore, the framework improves the worker's work life and work productivity. The discussed use case in section 4 explains the application of an IoT-based fatigue recognition system for recognizing the assembly line worker's fatigue status.

The preparation of an IoT-based fatigue status monitoring setup and the development of a worker fatigue status recognition function are critical for deploying the proposed methodology for a real assembly line. However, selecting appropriate sensors by considering their sensitivity, correctly placing sensors on the assembly worker, and maintaining and replacing sensors are critical for the IoT-based fatigue status monitoring setup. Preparation and selection of a learning-based fatigue recognition model and corresponding prediction accuracy are critical for worker fatigue status recognition function. Six learning models are prepared for the use-case illustration with the historical worker's fatigue response data (*i.e.,* Table 4). These are the Linear Regression, Polynomial SVM, Decision Tree, Random Forest, Naïve Bayes,



Emp. No	Emp. Name	Location	Assembly Tasks		Fatigue Status
xx	xxxxxxxxx	Workstation1	1,2		No
xx	xxxxxxxxx	Workstation2	3,4,5		Yes
xx	xxxxxxxxx	Workstation3	6,7		No
xx	xxxxxxxxx	Workstation4	8,9		No
xx	xxxxxxxxx	Inspection			No
xx	xxxxxxxxx	Packing			No
xx	xxxxxxxxx	Rework			No

Figure 7: Worker Fatigue Status Dashboard.

and Linear Discriminant Analysis models. Figure 5 shows their corresponding prediction accuracy. Since the learning data set is small and the corresponding prediction accuracy is low.

Making a historical worker's fatigue response data preparation system to make worker's historical fatigue-status data points (example Table 4), making an appropriate learning-based worker fatigue status recognition function, making a dashboard (*i.e.,* Figure 7) to see real-time fatigue status of all assembly line workers, improving the fatigue status recognition accuracy and verifying the proposed methodology for a large assembly line are the prospects to this research.

6 CONCLUSION

IoT-based intelligent work fatigue status recognition system framework is presented. The framework comprises a worker fatigue status recognition function, IoT-based status monitoring, and intelligent fatigue status recognition. Learning-based methods are used to make worker fatigue status recognition function. Sensor-connected IoT-based worker status monitoring system to monitor real-time status of the worker in terms of the worker fatigue status recognition function's factors. Finally, the intelligent system classifies the monitored status as 'Yes' or 'No' using the developed learning-based worker fatigue status recognition function. A use-case illustration is presented to demonstrate the proposed framework for a manual assembly line. Linear Regression, Polynomial SVM, Decision Tree, Random Forest, Naïve Bayes model, and Linear Discriminant Analysis model are used to make the worker fatigue status recognition function. The linear regression model has given better prediction accuracy compared to others. Making a historical worker's fatigue response data preparation system, making worker fatigue status recognition function with acceptable accuracy, and making a dashboard to see the real-time fatigue status of all assembly workers are the prospects for this work.

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