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Detection of Fall-Related Accidents Using Deep Learning Method in the Internet of Things

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ABSTRACT

Nowadays, with the increase in the number of employees in the enterprises and the proportional workload, different occupational accidents frequently occur. Examples of this are slippery floors, falling materials, harmful substances/gas leaks, improper use of protective clothing and equipment or not using them at all. Identifying these dangers and taking the necessary precautions are very important for both worker safety and employers. The most common accident among these dangerous situations is the accidents that occur as a result of slipping or falling. Such accidents are usually caused by a foreign liquid/substance on the work surface, the worker's inability to balance himself, or surface inequalities. With this study, an IoT and 1D CNN deep learning-based system has been developed to detect accidents such as falling, slipping and balance disorders to inform relevant health institutions. The developed 1D CNN-based system detected work accidents caused by falls with 100% accuracy. With the results obtained from this study, it is aimed to make improvements for the prevention of these accidents.

Nesnelerin İnternetinde Derin Öğrenme Yöntemi Kullanılarak Düşmeye Bağlı Kazaların Tespiti

ÖZ

Günümüzde işletmelerde çalışanların sayısının ve bununla orantılı olarak iş yükünün artması ile birlikte sıklıkla farklı iş kazaları meydana gelmektedir. Buna örnek olarak kaygan zeminler, düşen malzemeler, zararlı maddeler/gaz kaçakları, koruyucu giysi ve ekipmanların uygunsuz kullanılması veya hiç kullanılmaması bu iş kazalarına gösterilebilir. Bu tehlikelerin belirlenmesi ve gerekli önlemlerin alınması hem işçi güvenliği hem de işveren açısından oldukça önemlidir. Bu tehlikeli durumlar arasında en sık karşılaşılan kaza, kayma veya düşme sonucu meydana gelen kazalardır. Bu tür kazalara genellikle çalışma yüzeyindeki yabancı bir sıvı/madde, işçinin kendi dengesini kuramaması veya yüzey eşitsizlikleri gibi problemlerden kaynaklanmaktadır. Gerçekleştirilen çalışma ile düşme, kayma ve denge bozukluklarını gibi kazaların tespiti ve ilgili sağlık kuruluşlarına bilgi verilmesi için IoT ve 1D CNN derin öğrenme tabanlı bir sistem geliştirilmiştir. Geliştirilen 1D CNN tabanlı sistem düşme kaynaklı iş kazalarını %100 doğruluk oranında tespit etmiştir. Bu çalışmadan elde edilecek sonuçlar ile bu kazaların önlenmesine yönelik iyileştirmeler yapılması hedeflenmektedir.

Anahtar Kelimeler: Derin Öğrenme, Nesnelerin İnterneti, Sensörler, Düşme Tespiti

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1. Introduction

Workplace is a broad definition and covers a wide area from factories, construction sites to home environments. Dynamism is very high among the workplaces, especially in crowded and large workplaces such as factories and construction sites. These workplaces are areas that are very likely to have occupational accidents due to their dynamic structure. Occupational accidents are incidents that cause physical and mental damage in workplaces or places other than the workplace where the employee has gone due to their work [1,2]. In the past years, it has been revealed that work and workplace safety is very important in reducing occupational accidents and conducting a successful business [3]. The workplaces contain different hazards due to their many features such as constantly operating machines, variable physical barriers and hazardous chemicals. In Turkey, a total of 384 262 work related accidents occurred in 2020 and 1231 employees lost their lives as a result of these accidents [1]. The high numbers of occupational accidents show how important it is to prevent those accidents.

There are different accidents that occur as a result of different reasons in the workplaces. Some examples of these types of accidents are: work tools coming out of control, explosion or slipping of the materials in the work environment, injuries caused by the fall of the employees, etc. Among the workplace accidents, the one of the most common injuries are those that are related to the fall. In Turkey, during 2020, as a result of the explosion and breaking of the materials in the workplace 28.165 workers, as a result of the vehicles being out of control 54.217 workers were injured and the number of workers injured due to falling was 53.948 [1].

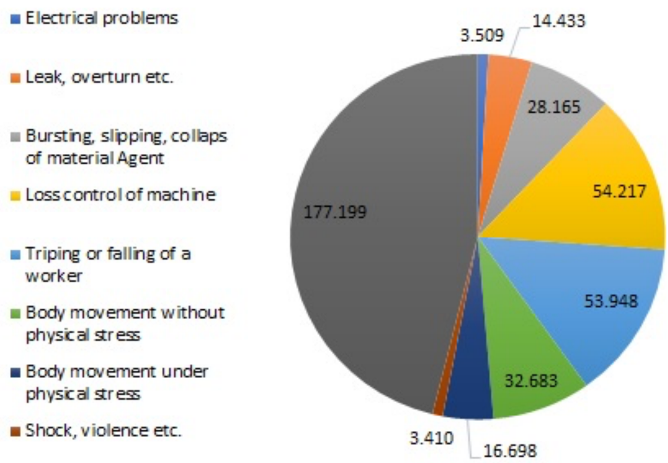

Figure 1. Occupational accidents in 2020 [1]

In Figure 1, the number of occupational accidents that occurred in 2020 and the reasons are given. As it can be seen in Figure 1, it is very important to determine the fall-related work accidents, which constitute the majority of injuries. The World Health Organization (WHO) defines fall as an event that causes a person coming to rest inadvertently on the ground or some lower level [4]. In Turkey in 2020, 215 out of 53.948 accidents due to falling resulted in the death of worker.

It is very important to react quickly to accidents caused by a fall as well as to identify these accidents. The faster the response to such accidents, the more the amount of deaths and permanent injuries caused by the accident will be reduced. It is difficult for employers with large numbers of employees to quickly find out that their workers have had an accident. For this purpose, Internet of Things (IoT), which emerged with the spread of technology and internet in the past years and shed light on the solutions of many problems, has been an important milestone in overcoming these difficulties [5].

IoT aims to enable sensors, people and environments to communicate and to make these tools a part of the internet environment [6,7]. The increasing use of the Internet with the spread of mobile devices has increased the popularity of IoT. Parallel to this the use of IoT in controlling industrial companies' working processes such as production, distribution, and transportation has also become widespread [8]. In addition to these areas of use in industry, IoT has begun to take its place in occupational safety as well [9, 10].

When the literature is analyzed, it is seen that many different methods are used for fall prediction. Kianoush et al. In their study, they developed a device-free prediction system using radio frequency (RF) signals to perform a fall prediction and to determine the location of the fallen person [11]. In the system, the returns of the RF signals that are continuously emitted to the environment are processed with the Hidden Markov model and prediction is performed. With their work, they achieved an accuracy of 98%. Hayat and Shan, on the other hand, made a fall prediction system by using an accelerometer [12]. The system created in the study sends a signal to the receiving side for help as a result of the acceleration values measured with the sensor exceed the determined threshold value. Lee et al. In their study, they preferred to use mobile phone instead of using an external sensor [13]. In the study, mobile phones were preferred due to their widespread use and they developed a special Android program for fall detection. They used SVM (Sum Vector Magnitude) for estimation and generally achieved an accuracy of 90%. In a different study made for iron workers, Kanghyeok et al. collected the data with wearable inertial measurement units (WIMU) and processed using the one-class support vector machine (OCSVM) algorithm [14]. As a result of the study, an accuracy of 87.5% was achieved.

2. Materials And Method

2.1. Materials

In the study, Arduino Micro development board and ATmega32U4 microcontroller were used. 6-axis MPU6050 accelerometer was used for acceleration measurement and Neo 6M GPS module was used for navigating the workers. The communication of the developed mobile system provided with the ESP8266 ESP-01 Wi-Fi module. In the study, the values taken from the accelerometer were first recorded on the SD card using the SD card module to create the data set. After that the recorded data are classified using the 1D CNN model.

2.1.1. MPU6050 accelerometer

MPU6050 is a 6-axis motion tracking device that combines 3-axis accelerometer and 3-axis gyroscope. In addition to these features, it has built-in Digital Motion Processor (DMP) [15]. MPU6050's gyroscope full-scale range is ± 250, ± 500, ± 1000, ± 2000 °/sec (dps), and accelerometer full scale range is ± 2g, ± 4g, ± 8g, ± 16g. In Figure 2, the orientation and polarity of rotation of the MPU605 can be seen.

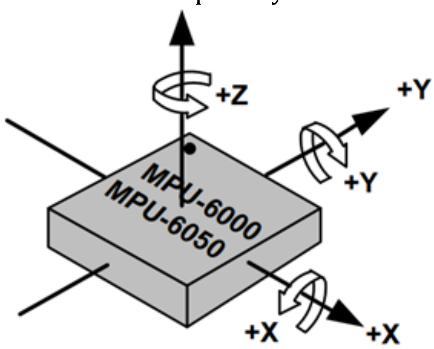

Figure 2. Orientation and polarity of rotation [15]

Communication is provided by Inter-Integrated Circuit (I2C-bus) protocol. Due to its small size and low energy requirement, the MPU6050 is often preferred in works such as wearable sensor and self-balancing robot [16-20].

2.1.2. Neo 6M GPS module

Neo 6M is an affordable GPS module with a size of 16 x 12.2 x 2.4 mm. Thanks to the acquisition engine with a 2 million correlator, the Neo 6M can make very large parallel time/frequency space searches [21].

2.1.3. ESP8266 ESP-01 Wi-Fi modüle

ESP8266 is a Wi-Fi module with integrated TCP / IP protocol stack and Wi-Fi Direct (P2P) support that helps systems communicate over the internet. With its affordable price, easy usage, small size and low (3.3V) energy requirement, it is a frequently used module in IoT applications. In this study, ESP-01 Wi-Fi module is preferred from ESP8266 types in order to take advantage of IoT features.

2.1.4. Dataset

The data used for the study were collected using the MPU6055 sensor and SD card. The waist area, which is the closest to the center of gravity in the human body and is minimally affected by hand and leg movements, has been chosen as the sensor location [22]. The location of the sensor on the body is shown in Figure 3.

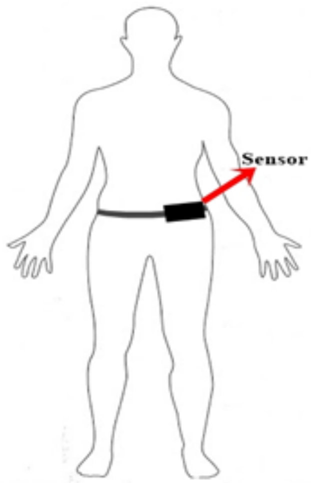

Figure 3. Placement of the sensor

Four different types of data were collected from five different people as falling forward, backward, right and left to cover all kinds of falling data. Only accelerometer data was collected from the MPU6055 sensor, and the resultant acceleration value was calculated using the values of the X, Y and Z axis collected from sensor and Equation 1. Sample of resultant accelerations calculated for walking, hanging and falling are shown in Figure 4. With this developed system, 50 data can be collected per second. Sample data was converted into signal form by taking 2-second resultant acceleration values.

$$R_{acc} = \sqrt{AccX^2 + AccY^2 + AccZ^2} \quad (1)$$

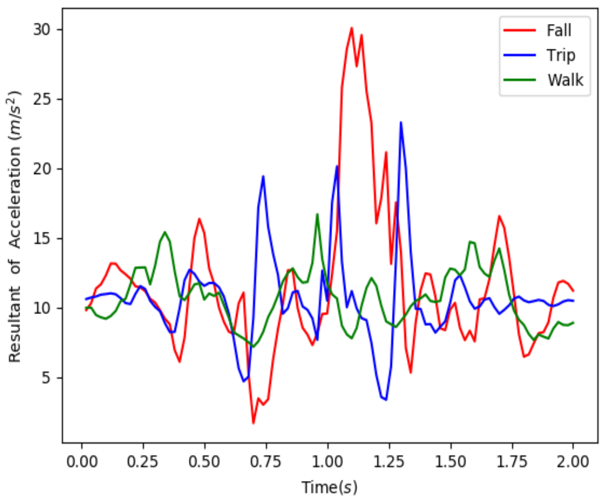

Figure 4. Sample resultant acceleration data

A total of 523 acceleration signals were used, including 132 falls, 98 trips and 293 walks. The distribution of signal data is given in Table 1.

Table 1. Distribution of the data used in the study (Çalışmada kullanılan verilerin dağılımı)

Data	Fall	Trip	Normal	Total
Train	96(%73)	67 (%68)	233(%79)	396
Valid	16(%12)	11(%12)	40(%13)	67
Test	20(%15)	20(%20)	20(%7)	60
Total	*132*	*98*	*293*	*523*

2.1.4. One-Dimensional convolutional neural network (1D CNN)

Convolutional neural network (CNN) is a method of deep learning that is frequently used in academic studies. There are different types of CNN models such as one-dimensional CNN (1D CNN), two-dimensional CNN (2D CNN) and three-dimensional CNN (3D CNN). 1D CNN is used on sequential data such as time series, 2D CNN in image processing studies, and 3D CNN on video and MR images [23].

The main difference between 1D CNN and 2D CNN is the size of the input variables. Because 1D CNN performs array operations instead of matrix operations, the computational complexity of 1D CNN is very low. For this reason, 1D CNN is frequently used in low-cost and real-time calculations [24]. Since the data used in 1D CNN is one-dimensional, the applied filter only shifts in one direction (Figure 5).

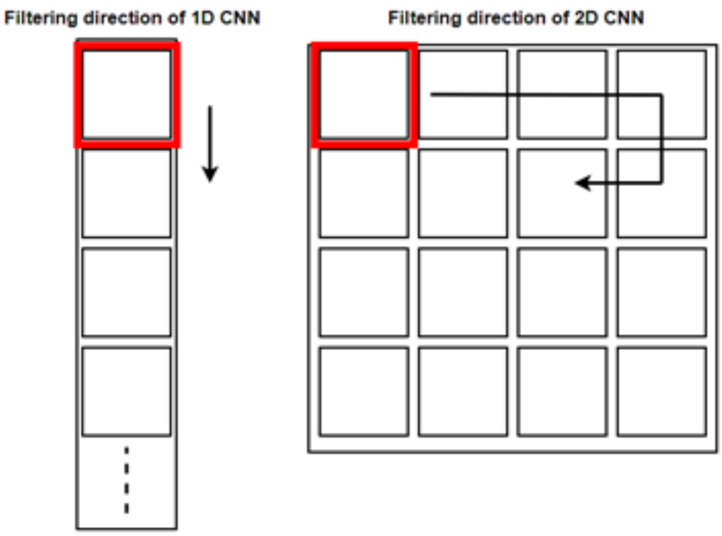

Figure 5. Filtering direction of 1D CNN and 2D CNN

In this study, 1D CNN method was used to evaluate and classify the data due to the type and properties of the data.

2.2. Method

Work flow diagram of the study is given in Figure 6. When Figure 6 is examined, it is seen that the study consists of two parts. In the first part, the data obtained from the MPU6050 accelerometer is modeled using the 1D CNN deep learning method. In the second part, the data from the accelerometer sensor is sent to a developed mobile application using the real time IoT method.

To carry out 1D CNN deep learning method; In the first stage, the data was recorded on the SD card using the MPU6050 acceleration sensor. In the second stage, which is the data preprocessing stage, normalization, loss data analysis and labeling operations are performed on the data and the data is prepared for the training process. In the third stage, a deep learning model was prepared by making use of 1D CNN layers. In Figure 7, the structure of the prepared deep learning model is given. When Figure 7 is examined, it is seen that the created model consists of 18 layers. In the input layer, an acceleration signal with a 100x1 size is given as input. The second and third layers of the model are convolutional layers, and the data are converted to 100x32 size by performing feature extraction. The fourth layer is one-dimensional maxpooling layer and the data is reduced to 50x32 size. The fifth and sixth layers are convolutional layers and feature extraction was performed on the data. The seventh layer is the maxpooling layer and the data size has been reduced to 25x32. The eighth layer, the convolutional layer, was used for feature extraction on 25x32 size data. At the output of this layer, the data size has been converted to 25x64. The ninth layer is the batch normalization layer, and the normalization process was performed by centering and re-scaling the data in a certain range. In the tenth layer, the convolutional layer, feature extraction was performed over 25x64 size data. The eleventh layer is the batch normalization layer, and the normalization process was performed by centering and re-scaling the data in a certain range. The twelfth layer is the convolutional layer, which is used for feature extraction on the batch normalized data. In the thirteenth layer which is the maxpooling layer, the data was reduced to 12x64 size. In the fourteenth layer, flatten layer, the data has been converted into one-dimensional data. This layer was used to prepare data for the neural network. At this layer data of 768 size was obtained as an output. In the thirteenth layer, which is the Fully Connected layer, training process continued with 128 neurons with 768 data obtained. In the fifteenth layer, dropout layer, 60% of the neurons are ignored during training to prevent overfitting. In the fully connected layer, the sixteenth layer, the training process continues with 32 neurons. In the seventeenth layer, which is the dropout layer, 50% of the neurons are ignored to prevent overfitting. The last layer, the fully connected layer, is the output layer. In this layer, the classification process is carried out. In the designed 1D CNN model, the training process of the model was carried out in the next stage. During the training, every epoch result was validated with validation data set. Training continued until the desired result was achieved. The model obtained was tested with the test data and the accuracy of the model was evaluated. As seen in Figure 8, in the second stage of the study, the data from the sensors were sent to the mobile application using the real time IoT method. First, the IP address, resultant acceleration signal and GPS coordinate data from the sensors are synchronously sent to the PC using localhost. From the data sent to the PC, the resultant acceleration data is passed through the created 1D CNN model and the estimation process is performed. A warning message is sent to the mobile application if the output from the 1D CNN model is fall or trip. In the mobile application, information about the IP number of the person, GPS location coordinates and acceleration of fall or trip are displayed.

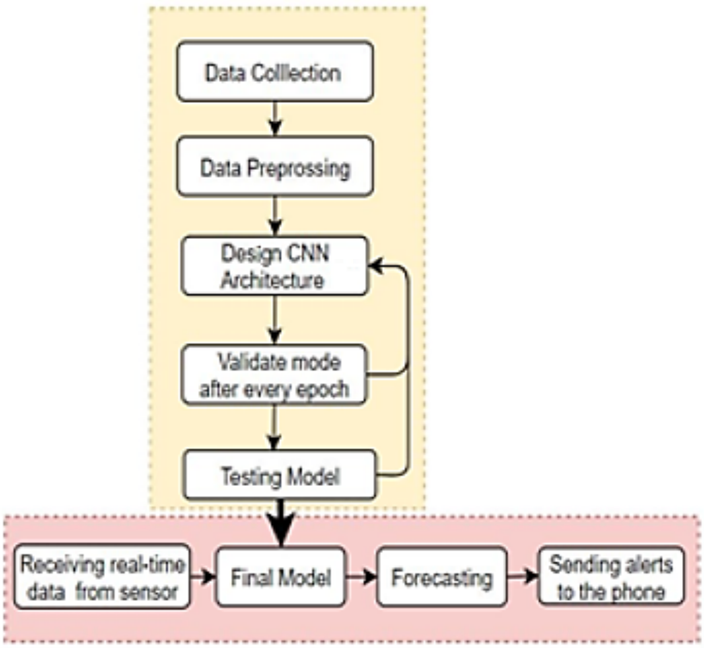

Figure 6. Work Flow Diagram

Table 2 presents the hyperparameters of the 1D CNN model created in the study. The learning rate was changed between 0.00001 and 0.1 and the learning rate value was selected in the area where the loss values decreased. The optimization method was chosen as Adam. Output activation function was preferred as Softmax due to conducting classification process. Epoch and batch sizes were determined by trial and error. In order to prevent excessive learning in the study, both fold cross-validation and validation of the model were validated with the dataset in the training phase. After the training, it was tested with the test data set. The trained model showed high performance on both validation and test datasets.

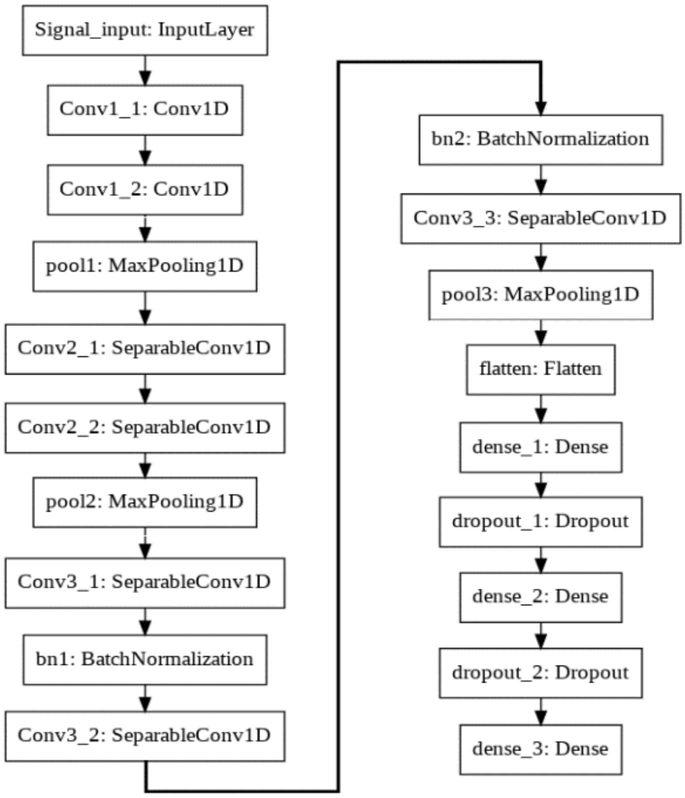

Figure 7. 1D CNN model used in this study

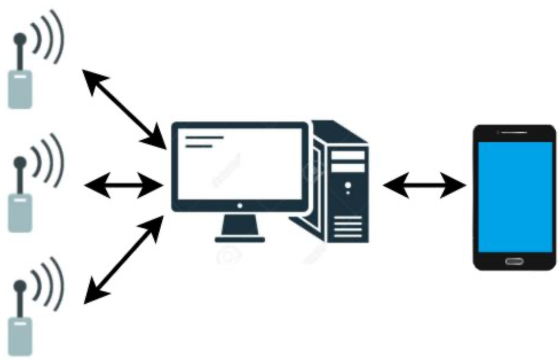

Figure 8. IoT architecture used in the study

Table 2. Hyperparameters of 1D CNN model

Hyperparameters	value
Learning rate	0.0001
Optimization method	adam
Input vector size	100
Output activation function	Softmax
Epochs	50
Batch size	16
Number of classes	3

3. Research Findings

In the study, the data received from the MPU6050 acceleration sensor is divided into three classes as walking, hanging and falling. In order to prevent overfitting of the 1D CNN model trained in the study, K-Fold cross-validation was used during the training phase. 76% of the data collected in the study was used as training, 13% as validation, and 11% as testing. The test dataset was never included in the model during the training process of the model, and the validation dataset was used to evaluate the model at each epoch. The accuracy of the model performed well on both the validation dataset and the test dataset. In addition, the model was evaluated using different performance evaluation criteria such as sensitivity, specificity, F1 score, AUC and ROC curve of the obtained model. 1D CNN deep learning model was created for classification. The Confusion matrix of the test data is given in Figure 9. When the confusion matrix is analyzed, it is seen that the 1D CNN model estimates falls, trips and walks with 100% accuracy using 60 tests data. The 100% accuracy rate obtained from the confusion matrix indicates that the created 1D CNN model was successful.

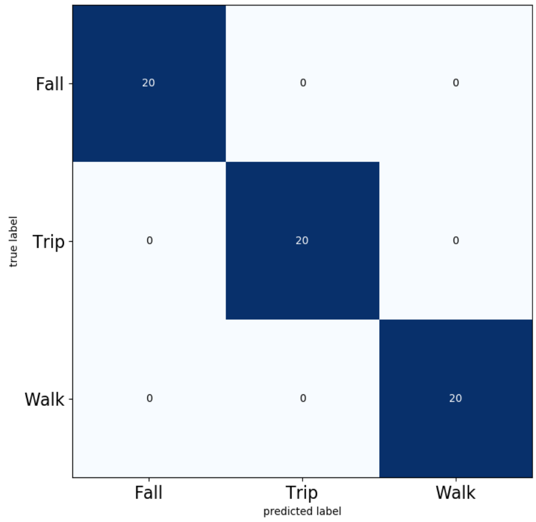

Figure 9. Confusion matrix of test data (Test verilerine ait karmaşıklı matrisi)

The results obtained according to ROC, AUC, Sensitivity, Specificity, Accuracy and F-Score performance evaluation criteria of the 1D CNN model created are given in Table 3.

Table 3. Results of 1D CNN model according to Performance Evaluation Criteria

AUC	**Sensitivity (%)**	**Specificity (%)**	**Accuracy (%)**	**F Score**
1.0	*100*	*100*	*100*	*1.0*

When Table 3 is examined, it is seen that the model works with 100% accuracy according to AUC, Sensitivity, Specificity, Accuracy and F Score performance evaluation criteria. Sensitivity, Specificity and F1 Score values given in Table 3 are the weighted average of all classes. The ROC curve of the 1D CNN model used in this study is plotted in Figure 10. When the curve is examined, it is seen that the ROC curve is almost the same as an ideal ROC curve. The fact that the ROC curve is very close to an ideal ROC curve indicates that the model is a successful model.

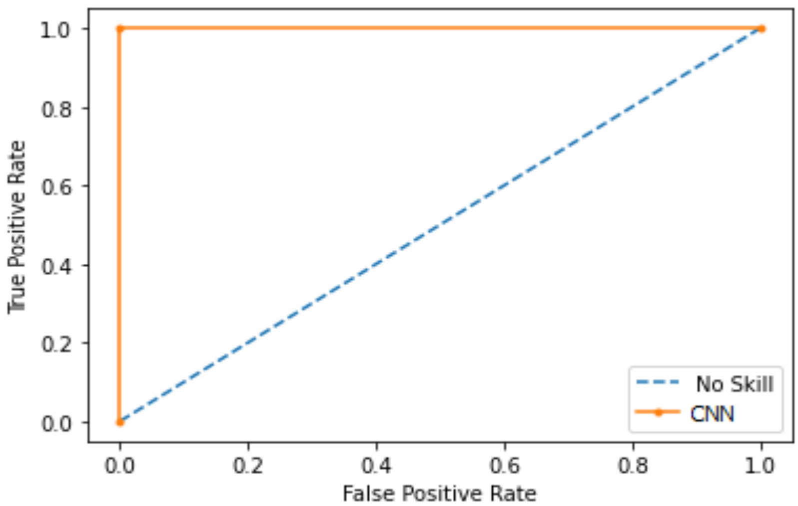

Figure 10. ROC curve of 1D CNN model

In Figure 11, the accuracy and loss values that occur during the training of the 1D CNN network used in the study are given. When the figure is examined, it is seen that the accuracy value of the model is constantly increasing and the loss value is constantly decreasing. This shows that the model is working correctly and there is no overfitting condition.

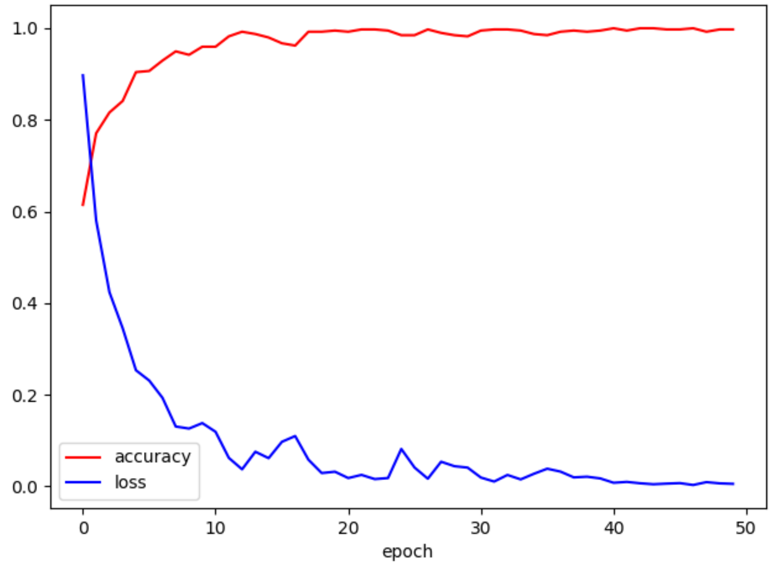

Figure 11. 1D CNN model training loss and accuracy

In the second stage of the study, the data received from the MPU6050 accelerometer was transferred to the PC via localhost. With the software developed in the Python programming language, the data received from the sensors are passed through the created 1D CNN network and classified as fall, trip or walk. When a fall or trip class result was detected, a warning message was sent to the mobile application containing GPS and IP address. In Figure 12, an example of the communication between mobile application and the sensor with the help of the PC is given.

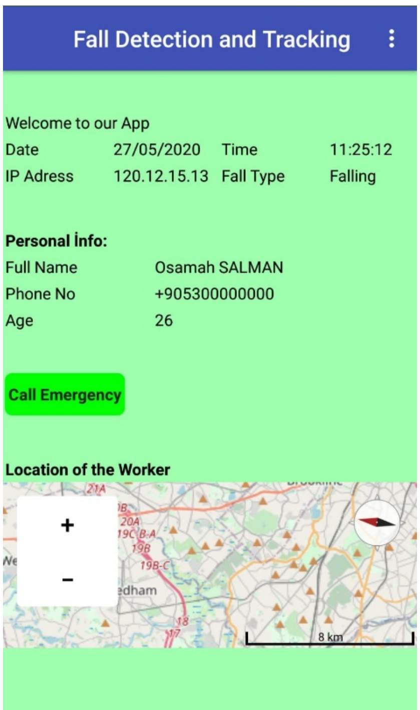

Figure 12. Sensor - Mobile application communication

When Figure 12 is examined, the data received from the sensor is sent to the mobile application after being classified using the 1D CNN model on the PC. As shown in the figure, Date, Time, IP address and

Fall Type variables are given in the upper region of the mobile application. In the middle part of the application, personal data of the person to which the sensor is connected is given. When the fall type feature comes to a value belonging to Fall or Trip class, the mobile application gives a warning message in the form of Call Emergency. At the bottom of the mobile application, the GPS coordinate information of the person to which the Sensor is connected is shown on the map. Using this map information, the location of the person can be determined.

4. Discussion

As a result of this study, the estimation and reporting of the accidents that occurred as a result of falling in the business areas was realized. The 1D CNN model created showed a 100% success in the fall and trip prediction. According to the results of the estimation, if the employee experiences an accident due to a fall, this information can be successfully transferred to the created mobile application over the internet.

With this study, it is aimed to reduce the permanent injuries and deaths that may occur by providing early detection and rapid reporting of accidents caused by a fall. The low false positive value obtained in this study supports its active use by increasing the confidence in the warning system. Systems with a high number of false positives in industrial use cause the system not to be taken seriously and even shut down afterwards.

The high accuracy rate obtained in this study reveals the success of the system. However, no matter how good the system is, unexpected situations may occur during the use of the system in real scenarios. Dynamic feature of the working environments may affect the accuracy rate. Examples of such things are the wearable sensor system being worn incorrectly by the employee, the diversity of people working in the workplace (height, weight, age, etc.), or connection problems that could interfere the communication of the system. The developed system detects the falls after they occur and can be used to respond quickly to the accident. Even if it is not possible to predict and completely prevent the accident before it happens, physical improvements can be made by tracking trips and falls from the same places.

In addition to these, collecting different data for different study areas and training the model with these data will increase the usage area of the model. Although the obtained 100% accuracy rate seems successful, it is estimated that this rate will decrease with the increase in the number and variety of data.

5. Conclusion

With the rapid advancement of technology, the use of software technologies and mobile devices are increasing. Artificial intelligence software has an important place among these software technologies. One of the important uses of artificial intelligence is occupational accidents. One of the most important points for security in industrial workplaces is to quickly locate the person who has an occupational accident. For this reason, fast and accurate detection of accidents caused by falls is very important. In this study, using the 1DCNN deep learning technique, a deep learning model for fall, trip and walk prediction was designed using the data obtained from the MPU6055 acceleration sensor. The results of the designed model are given below.

- In this study, the fall, trip and walking classification with the data collected from the MPU6050 accelerometer was classified using 1D CNN with 100% accuracy.
- The trained model was tested with 60 test data including fall, trip and walk, and the results were shown on the confusion matrix.
- The trained model was evaluated according to AUC, Sensitivity, Specificity, Accuracy and F Score performance evaluation criteria. All performance evaluation criteria yielded 100% accuracy.

In the second phase of the study, the data read from the accelerometer and GPS sensors were sent to the PC every 4 seconds synchronously. Since the acceleration data sent to the PC were taken in 2-second periods during the training, the classification process was performed by dividing the 4-second data into two parts and passing it through the one-dimensional CNN model. The following results were sent to the mobile application when a crash or fall was detected as a result of the classification process.

- Sensor IP address
- GPS coordinate information
- Fall type
- Employee identification information

In the study, artificial intelligence methods were used to detect occupational accidents caused by falls with the data obtained from the acceleration sensor. The artificial intelligence model has achieved a very successful result with 100% accuracy in detecting occupational accidents due to falls. The method used in the study is not only limited to accidents due to falls in the workplaces, but can also be used in rapid intervention to the accident in areas such as homes, hospitals and elderly nursing homes for the detection of falls.

In the future studies, dataset can be strengthened by collecting data from more diverse group of people for the development of this system. In addition, actions such as jumping, picking up objects, sitting may be confused with falling can be added to the dataset. To prevent communication problems, much stronger Wi-Fi modules can be preferred.

Ethics Approval

The study was carried out with the ethical approval of the Ethics Committee of Isparta University of Applied Sciences, with the decision dated 16.11.2020 and numbered 35/05.

Conflict of Interest Statement

The authors declare that there is no conflict of interest

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