ORIGINAL ARTICLE



Walking pattern analysis using deep learning for energy harvesting smart shoes with IoT

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Abstract

Wearable Health Devices (WHDs) benefit people to monitor their health status and have become a necessity in today's world. The smart shoe is the type of WHD, that provides comfort, convenience, and fitness tracking. Hence smart shoes can be considered as one of the most useful innovations in the field of wearable devices. In this paper, we propose a unique system, in which the smart shoes are capable of energy harvesting when the user is walking, running, dancing, or carrying out any other similar activities. This generated power can be used to charge portable devices (like mobile) and to light up the LED torch. It also has Wi-Fi-that allows it to get connected to smartphones or any device on a cloud. The recorded data were used to determine the walking pattern of the user (gait analysis) using deep learning. The overall classification accuracy obtained with proposed smart shoes could reach up to 96.2%. This gait analysis can be further used for detecting any injury or disorder that the shoe user is suffering from. One more unique feature of the proposed smart shoe is its capability of adjusting the size by using inflatable technology as per the user's comfort.

 $\textbf{Keywords} \;\; \text{Smart shoes} \; \cdot \; \text{Walking pattern} \; \cdot \; \text{Energy harvesting} \; \cdot \; \text{Wearable health device} \; \cdot \; \text{Deep learning} \; \cdot \; \text{Gait analysis}$

1 Introduction

Consumer dependency on wearable devices has grown rapidly in the past few decades [1]. As the wearable devices are now capable of monitoring the health of a person, they are now termed as Wearable Health Devices or WHDs. These devices provide data, wherein the device sends out suggestions on how one can improvise in their lifestyle for healthful living. Many devices like smartwatches, smart eyewear, fitness tracker, smart clothing are a few examples of WHDs. One such innovation in wearable health devices is smart shoes that are trending and evolving historically in the engineering field. Smart shoe is

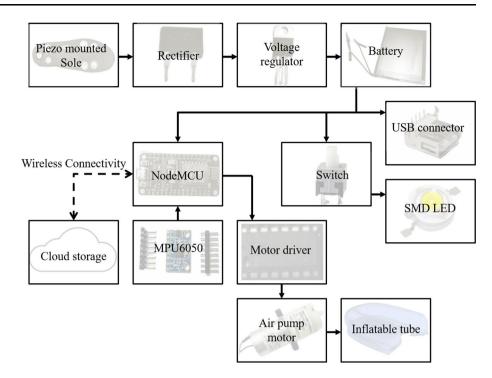
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K. J. Somaiya College of Engineering, Mumbai 400077, Maharashtra, India the technological innovation in the ordinary shoe with the high tech features that record biometric data and activities of the user. This data are recorded and transferred via Bluetooth or Wi-Fi, to mobile applications or computers for the analysis purpose. Devices like sensors, controllers, wireless devices, accelerometer [2], gyroscope, and magnetometer [3] are used for understanding the walking pattern and collecting data for the gait analysis [4]. As smart shoes are capable of monitoring the physical health and offering suggestions for improvement in the wearer's lifestyle, the need and demand for it is increasing day by day.

In this paper, along with keeping the track of user's health using IoT, harvesting electricity by walking, running, or carrying out other similar activities has been demonstrated. The power generation is done by using piezoelectric plates, which are placed at the base of the sole. As the user starts a normal activity such as walking or running, the pressure is applied on the shoe, utilizing this pressure, energy is harvested by the piezoelectric sensors that can be used to charge mobile phones, Bluetooth earphones, or other such similar devices. Figure 1 shows the proposed diagram of smart shoes. Energy is harvested,



Fig. 1 Block diagram of Energy harvesting smart shoes with IoT. The energy harvested from the piezoelectric crystals is stored in the battery, that is used to power up the NodeMCU, torch, and USB charging port. NodeMCU data obtained via MPU6050 was used to analyse the walking pattern of the user. An inflatable tube and air pump are used for achieving comfort fitting



when a person starts walking or running. A maximum output of 9 V is generated while running using these piezoelectric plates. Piezoelectric plates generate AC voltage that is converted to DC voltage by using rectifier. The DC voltage is given to the voltage regulator. The output of regulator is given to charge the battery. This battery provides power to LED via a switch, USB connector for external charging, and to the NodeMCU microcontroller. Accelerometer and gyroscopic sensor are interfaced to NodeMCU. The data are generated with the help of MPU6050 sensor, and it is transferred to ThingSpeak (cloud storage) via WiFI of NodeMCU. The sensor data are then displayed on the channel. The data were processed further for Gait analysis using deep learning. Another distinct feature of smart shoes is electronic autofitting using inflatable sole. L293d motor driver IC is used for driving the air pump motor. The air pump motor is used to inflate the tube according to the remaining space in smart shoes for comfort auto-fitting.

2 Literature review

At present many smart shoes have been developed [5–7]. In general, there are three main types of smart shoes: Electronic-based smart shoes [5, 8], Mechanical-based smart shoes, and Electro mechanical smart shoes. Electronic smart shoes can have micro-controller and sensors, wireless connectivity, and navigation system [9] inside it. There are multiple shoes reported in the literature for visually-

impaired [10] or physically challenged people. Bluetooth enabled smart shoes [11] are also developed. A big brand like Adidas [12] has developed smart shoes with intelligent cushioning with the help of magnet and sensor. The present manuscript takes advantage of all these reported technologies and further adds IoT functionality to transfer the data on cloud storage i.e., on ThingSpeak. The data were analyzed using deep learning for gait analysis. Mechanical smart shoes are passive pump-based smart shoes. The passive pump [13] technology allows customization of the shape of each shoe to fit the precise shape of each foot. The reported smart shoe has integrated an inflatable urethane bladder with an air compressor at the side of the shoe and a pressure release valve on the heel. All the technologies reported in the literature, has a manual air compressor, where user efforts of pressing the button consecutively are required. On the other hand, the shoes we designed can be adjusted electronically with a single press of a button; tubes are inflated automatically. Similar technology was reported by VectraSense smart shoes [14]. VectraSense presented a new computerized shoe named 'Verb for Shoe'. This footwear was skilled for sensing the user's activity level and automatically adjusting itself to improve comfort and performance. The shoes were integrated with an embedded computer that could learn the patterns and adjust the fitting according to the comfort of the user via the air bladder technology. The electro-mechanical smart shoes are of two types. The first one is the generator embedded into the smart shoes. These generators could be electromagnetic, piezoelectric, or solar panel-based [15]. The second type of



electro-mechanical smart shoe is motors induced inside a smart shoe to give a mechanical vibration. The reported generator embedded smart shoe has a solar panel generator along with a piezoelectric generator. The energy generated is used to charge the smart shoe battery. However, recently reported an electromagnetic generator and a piezoelectric generator [16, 17] are a more promising approach for energy harvesting as they can generate high output current level and voltage. With this consideration, we have used piezoelectric plates for the generation of power in our smart shoes. The power generated can even be used as a power bank to charge the other devices. The motor induced [6] inside a smart shoe is also reported in the literature. This motor is used for training foot progression angle during walking for the patients with osteoarthritis. There are some recent reports that use deep learning algorithms to determine the walking problem or walking pattern. Deep learning can also be used for classification [18–20].

3 Methodology

3.1 Hardware

NodeMCU was acquired from RS Electronics. MPU6050 sensor was purchased online from the element14 website. Air pump motor was acquired from robu.in which was used to inflate tubings inside sole, the tubings bought locally. Motor driver IC L293D was also acquired from robu.in, and it was used to drive the air pump motor. SMD LED (1 watt) was purchased from electronicscomp and used as a torchlight. Piezoelectric plates were purchased locally from Visha kits. USB connector was also purchased locally from Shanti electronics. Regular shoes were brought from Nike showroom of size 12. Battery and other small components such as copper-clad, FeCL3, etc. were purchased from Vega robokits. Insole and sponge were bought locally.

3.2 Softwares

Arduino IDE free software version 1.8.4 was used. Fritzing version 0.87 open source was used to design the PCB. ThingSpeak free web service was used to transfer data over the internet. MATLAB version 19b was used along with the Machine learning toolbox.

3.3 Shoes fabrication

Features we considered while designing the smart shoes were energy harvesting, LED as a torchlight, power bank, pedometer, walking pattern analysis (gait analysis), and auto-fitting (comfort using inflatable tube). Considering these features, the circuit designed with the help of

datasheets and interfacing diagrams. After designing the circuit, all the components were acquired. PCB designing was done using Fritzing software. Figure 2a shows the connection diagram of the components mounted on the breadboard. These connections were done as per the standard connection diagrams. Figure 2b shows the schematic diagram of the smart shoes. The schematic diagram consists of an MPU6050 sensor interfaced with the NodeMCU. Motor driver L293D interfacing with NodeMCU is also shown in Fig. 2b. Input to DB107 bridge rectifier IC is given from the piezoelectric sensor. IC7805 was used for voltage regulation. Single pole double throw (SPDT) switch was used to turn on or off the LED torch. The USB connector was attached for the charging of devices. Figure 2c shows the PCB layout of the designed PCB for smart shoes. PCB was designed using the Fritzing software and fabricated using standard negative photolithography and FeC13 etching process. Figure 3a shows the inner sole of the smart shoes. Plain rubber inner sole was converted into energy harvesting sole. Energy was harvested using piezoelectric plates. Maximum 9 V was generated from the piezoelectric plate and to increase the output current, 7 piezoelectric plates were connected in parallel. The electrical charge generated by applying mechanical stress on the piezoelectric sensor mounted on the inner sole was being converted to DC voltage with the help of the DB107 bridge rectifier. The converted DC voltage was further given to IC 7805. 7805 is a voltage regulator. It constantly gave 5 V output whenever the input DC voltage was more than 5.7 V. The output of 7805 was further given to charge the battery. The battery-powered the circuitry. SMD LED was being turned on or off using a SPDT switch. SMD LED was used as a torchlight in darkness or in the night. We were also able to charge the mobile using a USB cable plugged to the USB connector in the front of the shoes. MPU6050 sensor was interfaced with the NodeMCU microcontroller. The data were being generated with the help of the MPU6050 sensor. Figure 3b shows the final PCB of smart shoes fabricated, and components are mounted using a standard soldering technique. PCB is designed using Fritzing software. Figure 3c shows the assembly of smart shoes. The PCB was mounted directly inside the main bottom sole of smart shoes. The battery was attached to the PCB using a switch. The layer of sponge was placed in the remaining space of the main sole for protecting PCB from any damage. The inner sole with inflatable tubing was then sandwiched with the piezoelectric sole and placed on the top facing downwards. Figure 3d shows the final fabricated smart shoes. It was ready for testing and using. There was a slot on the front side of the smart shoe for LED and USB charging (Fig. 3).



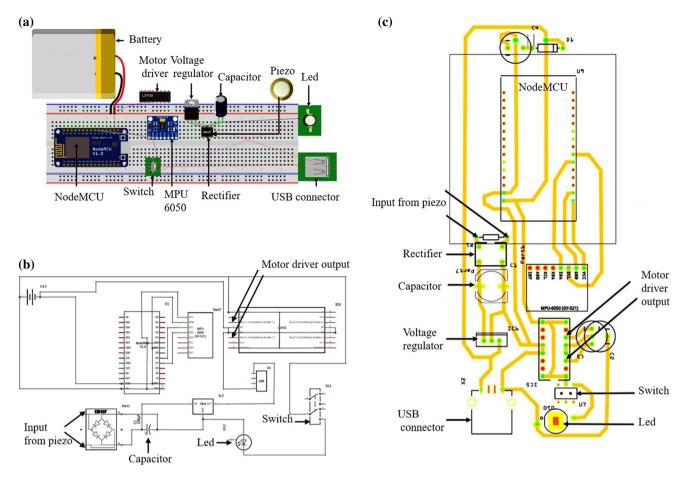


Fig. 2 PCB designing procedure of smart shoes using Fritzing. a Connection diagram of smart shoes on a breadboard using Fritzing. b Schematic diagram of smart shoes. c Final designed PCB layout of smart shoes

Fig. 3 Fabrication procedure of smart shoes. a Inner rubber sole converted to power generation sole using piezo. b Picture of fabricated PCB of smart shoes. c Fabrication of outer sole with the PCB, battery, and Inner sole placed on it. d Final fabricated smart shoes with inflatable sole and a slot for LED and USB charging in front

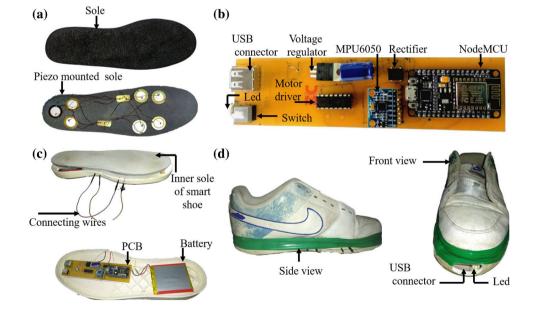




Fig. 4 The network diagram of 13-layer deep learning architecture. The network consists of an input sequence at the first layer, convolutional layers at the second, fifth, and eighth layer, batch normalization is at the third, sixth, and ninth layer. The fourth, seventh, and tenth layers consist of the rectified linear unit (ReLU) layer. The eleventh layer is a fully-connected layer with the twelfth layer as the softmax layer, and the last layer is the classification layer



3.4 Microcontroller programming

The microcontroller was programmed in C language. Arduino IDE software has been used for programming. Firstly, all necessary libraries have been included (Wire.h, ThingSpeak.h, ESP8266WiFi.h). For the WiFi communication ESP8266, the board package was installed from the board manager. The code for the MPU6050 sensor was developed using embedded C (refer to supplementary information S1 for the Code). Also, the API key (e.g., KWRY5OECU9TVAPAO) of the channel, created on ThingSpeak for receiving data from NodeMCU was mentioned in the code. The Service Set Identifier (SSID) and password for WiFi connection were integrated into the code for connecting and transferring the data from NodeMCU to ThingSpeak. SDA (data line) and SCL (clock line) pins were selected for I2C communication. We have set the sensitivity scale factor respective to the full-scale setting provided in the datasheet. Configuration of few register addresses of the MPU6050 sensor has also been done. We have set the field values of the MPU6050 for initialization. Code for writing to ThingSpeak channel, Updating channel, read raw values from the MPU6050 sensor was integrated with the main program code. Code works as follows:

1. On powering the NodeMCU, it will be connecting to the SSID network. 2. Reads the data from the MPU6050 sensor. 3. Field values are set of the MPU6050 sensor. 4. Writes it to ThingSpeak channel. 5. Updating channel every 5 s.

3.5 Deep learning algorithm for gait analysis

We have used 13-layer deep learning architecture for performing gait analysis. Figure 4 shows the network diagram of 13-layer deep learning architecture. The input data size



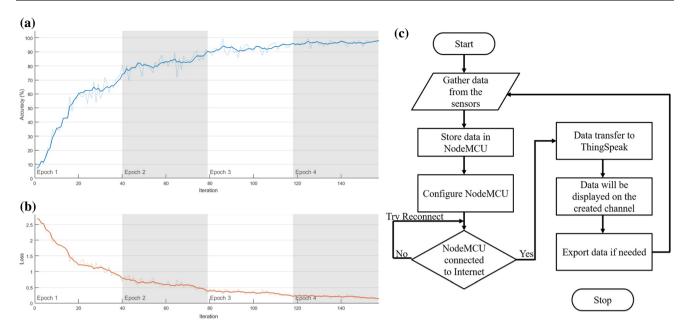


Fig. 5 Accuracy (a) and losses (b) plotted against iteration in deep learning networks. c Flowchart of smart shoe data transmission over IoT using cloud data service ThingSpeak

of 1×784 was obtained from the ThingSpeak channel and updated every second.

The first layer is the input sequence layer which uses zero crossings and truncation to find periodic patterns in received signals. The input data or walking pattern was given to this layer. The activation matrix is of size $784 \times 1 \times 1$. The second, fifth and eighth-layer is a convolutional layer. This layer applies convolutional sliding filters to the data. Each layer filters the data accordingly by creating the features of the map of the filter. The data of walking patterns are filtered into various maps. The activation matrix size was $784 \times 1 \times 32$. The weight matrix used was of the size $3 \times 3 \times 1 \times 32$, and the bias vector used was of the size $1 \times 1 \times 32$. The choice of these sizes was optimized initially between 16,32,64, considering time (best with 16) and accuracy (best with 64), we decided to use 32 as final value.

The third, sixth, and ninth layer is batch normalization. A batch normalization layer standardizes any input channel over a mini-batch. Using batch normalization, the processing time is decreased, and it also reduces the sensitivity to network initialization. The batch normalization activation matrix is of $784 \times 1 \times 32$. The offset and scale matrix is $1 \times 1 \times 32$. The fourth, seventh, and tenth layer is Rectified Linear Unit (ReLU) layer. A ReLU performs a threshold operation for each input variable, where any value that is less than zero is set to zero. The data from the tenth ReLU layer were fed to a fully connected network layer. In the fully connected layers, the input is multiplied with a weight matrix. After multiplying, a bias vector is also added to it. ReLU is used for activation in place of

other functions. The dimension of the ReLU activation matrix is $784 \times 1 \times 32$.

The eleventh layer is the fully connected layer. It extracts the data from all the layers for better classification. The activation matrix is of $1 \times 1 \times 8$, with a weight matrix of $8 \times 25,088$ and a bias vector of 8×1 . The twelfth layer is the softmax layer. It predicts a single class of various classes based on the training set. The dimension of the softmax activation matrix is $1 \times 1 \times 8$. The last layer is the classification layer. This classification layer measures the cross-entropy loss of mutually exclusive groups for 8 class classification problems.

3.6 Inflation for auto-fitting

For inflation, we have used a U-shaped soft elastomer tube made from Polydimethylsiloxane (PDMS). The PDMS is mixed with a ratio of 5:1 and poured on 3D printer mold made with water-soluble material of polyvinyl alcohol (Ultimaker PVA). Once the PDMS is cured after 24 h at room temperature, then the entire assembly was immersed into the ultrasonic water bath. Once the water-soluble mold is dissolved then the cured PDMS inflatable soft elastomer was used by connecting it to an air pump. The air pump motor (DC3V 030 air pump) inflates the tube. The pump is connected to the battery and was operated using a toe with a push switch. When the switch is in ON state, the tube inflates till it fits the wearer comfortably. This U-shaped soft elastomer tube is positioned on the front side of the inner sole. The inflation technique used in smart shoes possesses the auto-fit feature. These smart shoes are



designed such that, it can be worn by anyone with foot size from 6 to 10. The outer sole is of foot size 10. If the person with foot size 6 wears smart shoes, then the vacant space gets occupied by the inflated tube for comfort fitting.

4 Principle of tracking user's health

When the user starts walking or performing any other activity, the MPU6050 sensor collects the data as per the movement. This data will be transferred to ThingSpeak via NodeMCU. The data consist of readings of accelerometer parameters, temperature, and gyroscope parameters. ThingSpeak channel is updated every 5 s with the data collected from the MPU6050 sensor. The data are exported from ThingSpeak in (.csv) format. The exported data are further analyzed using a deep learning algorithm. After analysis, the walking pattern is obtained. The walking pattern obtained is compared further with the normal gait pattern. After comparing, it can be observed that the user's walking pattern is in a suitable range or not. If it's not in a suitable range then, it indicates that there are some problems at the early stage. This way the smart shoes help in keeping the track of a person's health.

5 Results and discussion

Figure 5a shows the plot of accuracy versus the number of iterations. As the number of iterations goes on increasing the accuracy of deep learning classification algorithms was saturated. We stopped after 4 epochs of 40 iterations each. After training the accuracy reached up to 96.2%. Figure 5b shows loss versus iteration plot. As the number of iteration and accuracy increases, the loss also goes down exponentially. We could achieve loss as low as 0.2 after 160 iterations. Figure 5c is of flowchart explaining the working of the smart shoes. Firstly, the sensor data generated by the MPU6050 sensor is gathered for further process. This data are temporarily stored in NodeMCU. NodeMCU is programmed and configured for a Wi-Fi connection. If the Internet connection is done successfully, then the data are transferred to ThingSpeak using API write key of the channel i.e., on the cloud server. The data transferred from NodeMCU to ThingSpeak will be displayed on the created channel. This data are further exported to MATLAB for further processing. If the NodeMCU is not connected to the Internet then the shoe will keep trying to reconnect until the data are transferred.

Classification accuracy is determined by the confusion matrix (Fig. 6). There are 8 desired classes and 8 predicted classes. The number of patterns in each desired class was 500, and hence we were expecting all the diagonal

elements (i.e., true positive) to be 500. We got a maximum of 498/500 in class 5 of the mid-swing class. whereas minimum accuracy appeared in the foot-flat class. It was expected because Mid-swing has very fewer chances of getting classified in either of the swings (i.e., initial and late) and also the negligible chance getting classified in any of the stance classes. We could figure out for proper reproduction of all classes at least 500 samples per second data were required. We set it to 784 samples per second. Also, FPS of ground truth video was required to be more than 500 frames, we have used 1000 FPS and dropped a few frames from the initial and the final part of the video to match the 784 frames to each sample. 5 such sample ground truths after binarization are attached in supplementary video SV1.

As shown in Fig. 6, the walking pattern is divided into 8 classes wherein, five classes are of stance phase, and three are of swing phase. Each phase represents a gait cycle of the walking pattern as the foot moves or touches the ground. The stance phase includes heel strike, foot flat, mid stance, heel off, and toe-off. The swing phase is further categorized as initial swing, mid-swing, and late swing. The heel strike stage is the first phase of the gait cycle wherein the heel of the first moving foot touches the ground. At the next phase, i.e., the foot flat phase the sole of the moving foot touches the ground. In the next phase i.e., mid stance, the leg of the first moving foot is perpendicular to the ground and momentarily stopped while the other leg moves forward. In the fourth phase, in the heel off stage, the heel begins to move away from the ground and for the fifth stage, in toe-off, the first moving foot leaves the ground while the sole of the other foot touches the ground. In the swing phase, the mid-swing is the step forward with the foot of the ground, and the late swing refers to the stage immediately before the next cycle begins. Along with all these standard 7 classes reported in literature, one initial swing class was also defined that corresponds to the initial pattern. The 5 gait phases were repetitive, and we needed to add visual recording to find out ground truths for comparison and supervisory training of deep learning network. The camera used was Sony Mark-V with 1000 FPS full of slow-motion recording (Refer supplementary video SV1). For generating ground truths for the corresponding signals, expert doctors from Ninad's research Lab and Kaushakya Medical foundation hospital were invited. The study was carried out on human subjects with their written consent.

5.1 Limitations

Along with the benefits of these smart shoes, there are some limitations in this study, which are discussed. In case there's no internet connection between the shoes and the



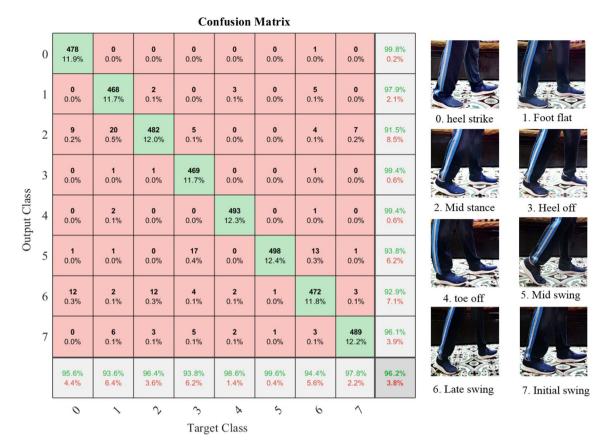


Fig. 6 Confusion matrix obtained during the testing phase of smart shoes. The walking pattern is classified into 8 classes, where 5 of them are classified into the stance phase and the remaining 3 are

device, the smart shoe won't upload data on the cloud or any other significant server. Hence, the walking pattern analysis won't be done for the time being. Smart shoes are not necessarily heavy; however, this particular model is heavier than regular sport or running shoes. In the event of constant activity by the user wearing the smart shoes, the battery might get overheated if excessively charged.

5.2 Future scope

The research doesn't end here and with day-to-day advances in innovation, the future scope for this technology is also seen, which is discussed. A solar panel can be added for the fast charging of the battery. Along with the existing sensors, a bonus night light sensor can be added for autoturning of LED in the dark. With the technology advancing rapidly, and people want everything on their smartphones, a mobile application can be developed for the shoe that connects with the user's smartphone and gathers all the data on it. This application can also be used for additional features such as connecting/disconnecting the Wi-Fi, the auto-inflation switch, and so on. Along with these features,

classified into the swing phase. Stance phase includes heel strike, foot flat, mid stance, heel off, and toe-off whereas swing phase has midswing, initial swing, and late swing

NodeMCU can be programmed to activate or deactivate the air pump motor for the auto-fit feature.

5.3 Commercial viability (production)

The production of the smart shoe is done in various steps such as; designing the sole, PCB, and finally the shoe. The manufacturing of the PCB, sole along with designing and the final product of the smart shoe should be in bulk. The inner and outer sole of the shoe can be designed using software like AutoCAD, CorelDraw, etc. For this product, the size of the outer sole will be fixed as the shoe incorporates the auto-fitting feature. The inner sole is embedded with the piezoelectric crystals to generate power. Similar to the outer sole, the inner sole is also designed as per the standard size. Hence, this saves the additional design of the different sizes of the sole. PCB designing can be done using software such as Eagle, Fritzing, etc. with the guidance of a circuit diagram. As the shoe requires two special soles, unlike the regular shoes, they can be developed by the manufacturer. Manufacturing of the PCB with the assembly of the components acquired from the vendors can be done by the manufacturer itself. Similar to the sole of



the shoe, the PCB is also designed in a standard size. This saves the developer from the additional designing, and redesigning of the PCB, if needed, and hence the manufacturer from producing different sizes of PCBs. This reduces the time, effort, and cost by a large sum during the production of the smart shoes. A sample 3D product, along with its blueprints of the soles and the PCB can be viewed on AutoCAD or CorelDraw. The shoes can be purchased from any local brand shoe store or may also be manufactured by the manufacturer together with the PCBs and the soles.

6 Conclusions

Smart shoes will be the next big thing in WHDs. The presented smart shoe could give a pathway for future research. Our smart shoes can generate power through piezoelectric plates, and it is stored inside the battery. This solves a big issue of the power bank. The generated power can be further utilized to glow the LED that helps the user to walk in dark. The data are logged by interfacing MPU6050 with NodeMCU, and it is sent to the ThingSpeak cloud via Wi-Fi. The deep learning algorithm used for the gait analysis can be further used for medical diagnosis. We believe the comfort fitting and auto-adjust with the inflatable tube was another unique feature of the work that we presented in this manuscript. It is the first time when someone combined multiple technologies and created a market-ready product for the consumer market.

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Declarations

Conflict of interest Authors N. Mehendale, N. Shah, and L. Kamdar declares that he has no conflict of interest also author D. Gokalgandhi declares that she has no conflict of interest aswell.

Human and animal rights This article does not contain any studies with animals performed by any of the authors. And also this article contain studies with human participants wearing the smart shoes. All the necessary permissions were obtained from Institute Ethical committee and concerned authorities.

Informed consent Informed consent was obtained from all the human participation who participated in wearing these smart shoes.

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