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Bedridden Disabled People's Monitoring System

R.R. Maghade[1], Saiprasad Darekar[2], Parth Jadhav[3], Aditya Shinde[4], Rushikesh Dahiphale[5]

[1]*Professor, Dept. of Computer Technology, P.Dr.V.V.P. Institute of Technology and Engineering, Loni, Maharashtra, India*

[2,3,4,5] *Final year Diploma Student, P.Dr.V.V.P. Institute of Technology and Engineering, Loni, Maharashtra, India*

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Abstract - People who are bedridden because of a disability, a long-term disease, or old age often have a hard time letting others know what they need and keeping them safe. Traditional caring approaches depend a lot on having somebody around all the time, which isn't always possible. This project offers a new Bedridden Disabled People's Monitoring System that will keep an eye on their health and safety in real time, make it easier for them to talk to each other, and improve the overall quality of care for people who are stuck in bed. The device uses a convolutional neural network (CNN) to keep an eye on how the body moves. It also has sensors that can tell you about the room's temperature, humidity, and air quality. Deep learning-based algorithms (CNN) can find strange patterns, such irregular heartbeats, sudden immobility, or indicators of distress, and send alerts to caregivers or healthcare experts right away through mobile notifications, alarms, or cloud dashboards. Caregivers can easily access live health data, get automatic alarms, and talk to the patient from a distance using a user-friendly interface. The system may have voice control, gesture recognition, or a single-button emergency call feature to make it easy for patients with restricted movement or speech problems to ask for help. Cloud-based storage makes sure that all the data that is collected is safely kept so that medical professionals can analyze it over time and make diagnoses from afar. This system uses cutting-edge technologies including the Internet of Things (IoT), wearable biosensors, wireless connectivity, and AI-based anomaly detection to make life easier for caregivers, make patients safer, and help find medical problems sooner. In the end, the suggested option gives bedridden impaired people the ability to keep their dignity, independence, and improved health while reducing stress for caregivers.

Key Words: Bedridden patients, Disabled people monitoring, IoT-based healthcare, Remote patient monitoring, Wearable biosensors, Deep learning in healthcare

1.INTRODUCTION

The fast growth of healthcare technologies and the growing need for patient-cantered care have changed how medical systems are built and used. Bedridden disabled people are one of the most vulnerable groups that need particular medical care. Because of physical limitations, long-term diseases, or issues that come with age, these people often have to stay in bed for long periods of time. This means they need help from caregivers and healthcare workers for even the most basic things. Traditional healthcare support systems, while necessary, often fall short in delivering continuous, real-time monitoring and individualized treatment to this demographic. Because of this, it is still very hard to find medical emergencies quickly, have a good quality of life, and deal with emotional stress. The Bedridden Disabled People's Monitoring System tries to solve these problems by bringing modern technologies like the Internet of Things (IoT), artificial intelligence (AI), and convolutional neural networks (CNN) into healthcare. This kind of device makes sure that vital signals like heart rate, body temperature, oxygen saturation, blood pressure, and movement patterns are always being collected. Caregivers, family members, and healthcare providers can see the data in real time, so they can act right away if something is wrong. Switching from reactive to proactive monitoring can save lives, save the cost of hospitalization, and make both patients and their families feel safer.

People who are bedridden are not only physically limited, but they are also mentally affected by being alone, relying on others, and having less contact with others. Voice help, alarm systems, and communication interfaces can all improve smart monitoring systems. This lets patients quickly say what they need without having to rely on physical interactions. For instance, patients can use AI-based voice recognition or gesture detection to ask for help with food, water, or medical care. Additionally, powerful machine learning algorithms can use past data to find possible health hazards, which can warn doctors and caregivers about serious problems like respiratory failure, pressure ulcers, or irregular heart rhythms before they happen. The increasing number of older and disabled individuals around the world makes these systems even more important. Global health surveys say that the number of disabled and elderly people who need long-term care is gradually rising. This is because people are living longer, cities are growing, and health problems related to lifestyle are becoming more common. Without the help of technology, the load on caregivers and healthcare facilities is becoming too much to handle. So, using smart, automated monitoring devices not only improves patient care, but it also makes caregivers' jobs easier and makes healthcare more efficient.

Another important part of this concept is that it might work with cloud computing and mobile apps. Healthcare providers can access patient information at any time from cloud servers that securely store data received by sensors. Caregivers get fast alerts regarding crises such rapid reductions in oxygen levels, strange body movements, or long periods of inactivity through mobile notifications and dashboards. Emergency warnings can also be delivered straight to neighbouring hospitals or family members, making sure that medical help is available quickly. The Bedridden Disabled People's Monitoring System is also in line with the global idea of "smart healthcare" and telemedicine, which are becoming the new norm for remote monitoring and real-time diagnosis. The COVID-19 epidemic made it clear that we need remote healthcare solutions right once. Many patients had trouble getting to hospitals because of lockdowns and a lack of resources. This demand is considerably stronger for people who are bedridden or disabled, which is why these kinds of monitoring devices are not only useful but also necessary in today's healthcare system.

The system can be set up using a mix of wearable medical sensors, IoT modules, wireless communication technologies (such Wi-Fi, Bluetooth, or ZigBee), cloud platforms, and AI algorithms. A wearable pulse oximeter can keep track of oxygen saturation levels, while pressure sensors built into a bed can keep an eye on how a patient is moving and stop bedsores from forming. AI-powered analytics make it possible to predict, find anomalies, and make smart decisions. This makes sure that the system keeps learning and getting better. This kind of system is important for more than just health reasons; it also protects people's dignity and quality of life. For many people with disabilities, not being able to say what they need or how they feel can be very frustrating and lead to neglect. This technology encourages inclusivity and lessens the feeling of powerlessness by giving users an interactive monitoring framework that fills in communication gaps. Families of patients also feel better knowing that their loved ones are being watched all the time, even when they
aren't there.

The Bedridden Disabled People's Monitoring System is a complete system that brings together healthcare, technology, and compassion. It uses IoT, AI, and real-time connectivity to keep an eye on patients all the time, respond quickly to emergencies, and improve their quality of life. As more disabled and bedridden people need help with their healthcare, these systems will be very important for lessening the strain on caregivers, lowering healthcare costs, and making sure that vulnerable groups get the care and respect they need when they need it. This project is not only a technological breakthrough, but it also shows a commitment to helping people by making healthcare more accessible, efficient, and patient-friendly.

[1] M. Hudec et al. applied study in the field of UI design for individuals with blindness (2014–2023) indicate that they can be competitive with sighted workers in the chosen occupation. Consequently, the contribution of this study is both technological and social in nature. The primary scientific contribution of this study is to expand the knowledge base about advanced UI design principles for individuals with blindness, which is essential in professional contexts where they must compete with sighted colleagues. The main practical contribution of this article is to give tips on how to build UI for blind people, with a focus on speed, dependability, and accuracy of control. The article also talks about new job prospects for blind individuals that will come up as more people work from home. There hasn't been any scientific research yet on how to make sure that workers who are blind can compete with individuals who can see in computer-related fields.

[2] Muhammad et al. know that DL-based methods like DNN, RNN, and SNN have big performance and computational problems. We suggest using randomized-based techniques like ELMs and RVFL instead, which are more efficient. By adding unpredictability to the training process, these strategies made it easier to compute and faster to train while still getting good results. We applied all the evaluated methodologies in two distinct case studies: predictions of genitourinary cancer and predictions of coronary artery disease.

[3] M. H. Abidi et al. presents; DEL comes from its amazing capacity to deal with the complexity and

variety of healthcare data. DEL is a way to combine different deep learning models, like CNN, LSTM, DNN, and DBN. Each of these models is great at a different part of data processing, which makes them quite useful for keeping an eye on health. The suggested system's DEL will use the collective intelligence of these several models. DEL makes the system stronger and more reliable by putting them together. This is especially critical when keeping an eye on health care, as data might show complicated patterns and changes. DEL reduces overfitting, which is a typical problem in deep learning, and therefore improves generalization, making sure that the suggested system can make good predictions even on data it hasn't seen before. HDCO is an important part of the proposed system. It is in charge of fine-tuning the parameters of the integrated models in DEL. Its job is quite important for making the models work better and more efficiently. HDCO makes sure that the individual models work at their best when they are put together in an ensemble by methodically exploring the parameter space. This optimization method is very important for making accurate predictions. HDCO not only makes the system work better, but it also makes it more flexible, so we can keep up with changing data and keep it running at its best.

The subsequent section of this paper analyzes the previous studies that were classified as "Literature Surveys." Section 3 provides a comprehensive description of the proposed methodology. Section 5 investigates potential modifications, while Part 4 delves into the experimental evaluation. The article concludes with a summary of the current proposal.

2. LITERATURE REVIEW

[4] S. Abbas et al. focused on models with a lot of labelled data, as mentioned. In the future, it might be useful looking into ways for the model to learn even when there isn't a lot of labeled data. Lastly, it would be crucial for future study to evaluate the models in real healthcare settings to discover how they affect the health and well-being of older persons. This study examined the recognition of daily activities performed by older persons to enhance healthcare and assess their well-being. This research utilized the dataset "HAR70+" to analyze the everyday activities of older persons, employing machine learning (ML) and deep learning (DL) approaches to develop robust predictive models for these activities. The study employed models such as KNN, LR, NB, RF, SGD, XG Boost, and LSTM, all of which demonstrated favorable outcomes. The models had variable accuracy, F1 scores, recall, and precision throughout three tries. The LSTM model had the highest average accuracy of 0.9861, which means it did the best. In conclusion, our research demonstrates that training machine learning (ML) and deep learning (DL) models to comprehend the behaviors of older persons is essential, as it can enhance their healthcare and support.

[5] A. Sundas et al. highlighted that the SPMR system keeps track of people with chronic illnesses who live far away, such diabetes and high blood pressure, in real time. The local and cloud versions of this framework are equally good at predicting important occurrences like power outages and natural disasters. We were able to reduce the difference between the projected and real label error rate by using a new CCE optimization method along with a new DL method. Uniqueness makes it more likely that the DL algorithm will converge quickly. We are doing ground-breaking work since we use a cloud-based prediction algorithm on GCP to find huge datasets. Our research team has proven that deep neural networks can be quickly and easily set up on local PCs using deep learning tools like Scikit-learn, TensorFlow, and Keras. The presented framework could be utilized to construct different deep learning algorithms in the future. The proposed context-aware framework will also be used to assess other long-term illnesses, like cancer.

[6] Yang et al. This study presents a mathematical model for enhancing automatic assisted repositioning tactics through the integration of inverse modelling, nodal equivalence techniques, and finite element methods. The results show that moving at a 30° angle significantly lowers pressure concentration. This gives a lot of theoretical support for the design and improvement of automated aided turning nursing beds and repositioning methods. This finding adds to earlier research that suggests a 30° tilt makes the buttocks more comfortable and has little effect on vital signs . This makes the case for the effectiveness and safety of this turning approach even stronger. Our biomechanical model also provides a useful way to find the best turning angles, which shows that it can be used in real life. The successful use of this model also makes it possible to use mechanical analysis in additional high-risk regions for pressure ulcers (PUs), like the shoulders and feet.

[7] Amer Tahseen Abu-Jassar et al. It is very important to add the present RPMS to the Medicine 4.0 architecture. By solving this problem, we can make it easier and more automatic to get biomedical information about a patient's health, as well as prevent and treat chronic diseases, viral pandemics like SARS-CoV-2

(COVID19), and swine flu A/H1N1 from a distance. This is possible because we can monitor the patient's current indicators and provide medical care. The study focused on existing and commercially available portable patient monitors for the measurement of biological data. The examination of technical specifications and attributes uncovered numerous shortcomings, including excessive dimensions, reliance on thermal printers for data output, and restricted implementation of Internet of Things technologies. Consequently, several responsibilities were allocated for the formulation of a new RPMS strategy within the Medicine 4.0 context. The novel idea was based on using cloud services, the Internet of Things, machine-to-machine, and microprocessor systems to get, process, and analyze biomedical data. Based on the proposed idea, the structure of the remote patient monitoring system was created, the hardware modules and sensors for the experimental prototype were chosen and analyzed, a schematic for connecting all the parts was made, and an experimental test prototype using the BME280 sensor was put together.

[8] P. S. Addison et al. The findings presented in this study demonstrate the feasibility of continuous non-contact monitoring for assessing the I:E ratio, which we anticipate could evolve into a significant advancement in respiratory monitoring when non-contact patient monitoring techniques gain broader accessibility.

[9] F. Zeshan et al. Presenting, Emergency services are important for every society to save lives of their citizens. These technology-based solutions are very complicated and complex due to the involvement of several factors like networks, artificial intelligence, knowledge engineering and system engineering etc. In this regard, internet-based technologies have played a major role to interconnect independent devices in an efficient and economical way. However, to deal with complexity (het erogeneity in terms of device data, languages and operating platforms etc.) and to develop dynamic, flexible, and cost-effective system, the semantic web can be used. Semantic web relies on ontologies which presents the data along with schema in an independent and machine processable format. To develop an ontology based IoT healthcare systems researchers have proposed several solutions with few shortcomings. For example, lack of agility, performance of devices and the accuracy of decisions. This research has proposed an ontology-based healthcare framework to organize the terms for describing the patients in a formal way.

[10] N. Ahmad et al. for WBAN, they made the QoS Aware Routing Protocol (IM-QRP) better. The suggested protocol may choose the best route and greatly extends the life of the network by arranging sensor nodes and relay nodes on the human body based on how the patient moves. The primary contribution of this research is the enhancement of Quality of Service (QoS) offering. Better residual energy in sensor nodes and a higher SNR make the whole network's link dependability stronger. The strong connection stability makes the RSSI better, which lets the most packets reach the receiver side (sink node). Simulations in MATLAB are used to test the proposed protocol. The QRP protocol is compared to the QPRD and CO-LEEBA protocols. The IM-QRP protocol significantly enhances residual energy, quality of service (QoS), reduction of route loss, and signal-to-noise ratio (SNR). The next study will focus on combining the suggested WBAN framework with smart houses by using an Internet of Things (IoT) based framework.

[11] Díaz-Jiménez et al. offers d a unique methodology for sensor-based adherence platforms meant for home monitoring of KTIs. The work centers on three primary objectives: 1) the introduction of a tailored methodology for the creation of adherence computing platforms, facilitating the monitoring of healthy behaviors in various patient residences; 2) the development of a specialized platform for the oversight of diabetic patients, all within the context of the aforementioned methodology; and 3) the initiation of reflective discourse regarding prospective research trajectories and the challenges inherent in the implementation and enhancement of these adherence computing platforms. During the creation of the work, there has been a lot of focus on getting diverse people involved in the process so that the solutions are useful, effective, and easy to get to. We also compared the proposed platform for diabetes with the numerous adherence platforms on the market.

[12] A. Khalifeh et al. describes a framework for healthcare monitoring services that is made up of many systems. In this architecture, patients get sensors that keep an eye on their health and communicate the data they collect across a wireless communication channel to a remote unit for more analysis and action. To give patients a dependable and effective system, a strong wireless communication protocol is suggested. This protocol makes sure that the sensor nodes are reliable while also taking into account the channel conditions and the priorities and importance of the sensors. For example, more error correction bits and more network

access time are given to the more important sensors. In our future work, we will try to find the best number of error correction codes to give each sensor, taking into account things other than the channel condition, like the sensor's battery level and the state of the wireless network. We are also working on making a prototype of the suggested framework and testing the proposed wireless protocol in a lab.

3. METHODOLOGY

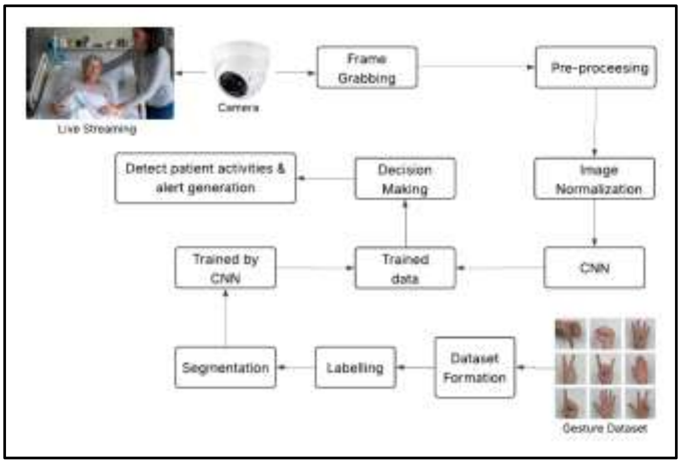

Figure 1: Overview Diagram

The proposed methodology for the Bedridden Disabled People's Monitoring System is implemented using deep learning techniques and real-time monitoring. The system performs patient activity detection and alert generation using live video streaming and gesture analysis. The overall workflow of the system is illustrated in Figure 5.1 above, and the detailed steps are explained below.

Step 1: Frame Grabbing and Pre-processing

The first stage of the system begins with live video streaming using a camera. The camera continuously captures video frames of the patient using OpenCV. These frames are then passed to the frame grabbing module where individual frames are extracted from the live stream.

After capturing, the frames undergo preprocessing. In this stage, unnecessary noise is removed, and the region of interest (patient body or gestures) is extracted. Image normalization is then performed to resize the frames into a fixed dimension suitable for further processing. Additionally, grayscale conversion is applied to reduce computational complexity while preserving essential features. This ensures that the input data is consistent and ready for the deep learning model.

Step 2: Image Normalization and Dataset Formation

Once preprocessing is completed, the images are normalized and structured into a dataset. The dataset contains different patient activities such as hand movements, gestures, or abnormal body positions.

The collected data is then organized into labeled categories. Each image is assigned a label based on the activity it represents. This dataset is further divided into training and testing sets. Proper dataset formation ensures that the model learns effectively and improves its prediction accuracy.

Step 3: Image Segmentation and Labelling

In this stage, segmentation is performed to isolate important regions such as hands or body parts from the background. This improves the accuracy of detection by focusing only on relevant features.

After segmentation, labeling is carried out where each segmented image is tagged with its corresponding activity class. This labeled dataset is essential for supervised learning in the CNN model. The segmentation and labeling process helps in building a high-quality dataset for training.

Step 4: Convolutional Neural Network (CNN)

This is the core component of the system where deep learning is applied for activity recognition. The prepared dataset is fed into the CNN model for training.

The CNN processes the input images through multiple layers such as convolutional layers, pooling layers, and fully connected layers to extract important features. The model is trained using the labeled dataset to recognize different patient activities accurately. After training, a model file (in .h5 format) is generated, which is used for real-time predictions.

Layer	Activation
CONV 2D 32 X 3 X 3	Relu
CONV 2D 64 X 3 X 3	Relu
MaxPooling2D 2 X 2	
Dropout 0.25	
CONV 2D 128 X 3 X 3	Relu
MaxPooling2D 2 X 2	
CONV 2D 128 X 3 X 3	Relu
MaxPooling2D 2 X 2	
Dropout 0.25	
Flatten	
Dense 1024	Relu
Dropout 0.25	
Dense 5	Softmax
Adam Optimizer	

Figure 2: CNN Network Architecture

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Step 5: Decision Making and Alert Generation

After training the CNN model, the system moves to real-time implementation. The live video feed is continuously processed, and frames are passed through the trained CNN model.

The model predicts the patient's activity based on the learned patterns. If any abnormal activity is detected (such as no movement, unusual gestures, or emergency signals), the system triggers an alert.

The decision-making module analyzes the prediction score, and if it exceeds a predefined threshold, an alert is generated. This alert can be sent to caregivers or medical staff for immediate action.

Step 6: Patient Activity Detection

Finally, the system continuously monitors patient activities and ensures safety. It detects movements, gestures, and inactivity in real time. Based on the analysis, necessary alerts are generated, making the system reliable for monitoring bedridden and disabled patients.

4.RESULT AND DISCUSSION

The approach proposed for the Bedridden Disabled People's Monitoring System has been successfully implemented using Python programming language with Spyder IDE. The system utilizes deep learning frameworks such as OpenCV, TensorFlow, and Keras for patient activity recognition. The implementation was carried out on a system equipped with an Intel Core i5 processor, 8 GB RAM, and 1 TB storage.

The proposed model was trained for 500 epochs considering five different patient activities, namely Thirsty, Hungry, Uneasy, Pee, and Loo. The outputs obtained from the model were analyzed to evaluate the overall system performance and effectiveness in real-time monitoring.

To evaluate the accuracy of the proposed system, the error between correctly identified activities and incorrectly identified activities was calculated. The reliability of the system depends on minimizing this error. For this purpose, the Root Mean Square Error (RMSE) metric is used as an effective performance evaluation measure.

The RMSE is calculated using the following formula (1):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(Z_{fi}-Z_{oi})^2}{N}}............(1)$$

Where:

- Z_{fi} represents correctly identified activity
- Z_{oi} represents incorrectly identified activity
- N represents number of experiments

A total of 10 iterations were performed for each of the five activities. The results obtained from these experiments were recorded and used to compute the error values. Based on the observed incorrect identifications, the Mean Square Error (MSE) values were first calculated and then used to analyze system performance.

Gesture	Number of Iterations	Correctly Identified Activity	Incorrectly Identified Activity	MSE
Thirsty	10	9	1	1
Hungry	10	8	2	4
Uneasy	10	9	1	1
Pee	10	7	3	9
Loo	10	10	0	0

Table 1: MSE/RMSE outcomes for 5 patient activities

The obtained results show that the system performs efficiently for most of the activities. The activities such as Thirsty and Uneasy show very low error values, indicating high recognition accuracy. The Loo activity achieved zero error, which means it was perfectly recognized in all iterations. However, activities like Hungry and Pee show slightly higher error values due to similarities in gesture patterns or environmental variations.

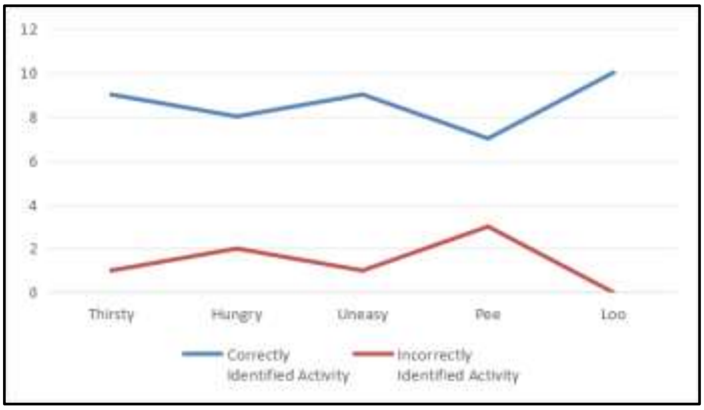

Figure 3: Line Graph for MSE outcomes

The graph plotted based on the obtained error values shows a clear variation in error across different activities. The lower error values indicate better performance of the model. The overall average error remains low, demonstrating that the proposed deep learning model is effective in recognizing patient activities.

The improved accuracy of the system is mainly due to the use of Convolutional Neural Networks (CNN), which enhances feature extraction and classification capability. The system achieves reliable performance with low error rates, making it suitable for real-time monitoring of bedridden and disabled patients.

Overall, the obtained results confirm that the proposed system is efficient, accurate, and capable of assisting caregivers by providing timely alerts based on patient activities.

5. CONCLUSIONS

The Bedridden Disabled People's Monitoring System provides an effective solution for improving the quality of life and safety of individuals who are unable to move or care for themselves. By integrating IoT, CNN and alert mechanisms, the system continuously monitors vital parameters such as heartbeat, body movement, and temperature. This real-time data helps caregivers and healthcare professionals respond immediately to any abnormal conditions or emergencies. The system also reduces the dependency of patients on others for constant supervision, ensuring they receive timely assistance when needed. Moreover, it minimizes the chances of unnoticed health deterioration by providing instant notifications and data logging for medical analysis. The automation and efficiency of the system reduce the workload of nurses and attendants while enhancing overall healthcare management. In the long run, such technology-driven solutions contribute to better patient care, safety, and dignity. Hence, the Bedridden Disabled People's Monitoring System stands as a vital innovation in modern healthcare for disabled and bedridden individuals.

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