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Original Article

Intelligent Decision Support System for Personal Healthcare

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ABSTRACT

In India, adultery is punishable by up to five years in prison under Section 497 of the Indian Penal Code, 1860. The first reaction upon seeing reality is one of shock at the State's blatant intrusion into what appear to be private sexual spheres. Specifically, to determine whether there are any moral justifications for making adultery a crime. My focus is on the paper's main argument, which is that the Legislature should repeal Section 497 because it, among other things, enacts detrimental gender segrWearable consumer technology has advanced to a point where it now dominates the healthcare industry. In complex IoT environments, there is a constant need for reliable recognition of diverse human behaviors. Applications in healthcare will subsequently be integrated with the knowledge gained from these recognition models. The four stages of the suggested framework are application creation, performance analysis, deep learning model deployment, and dataset and processing utilization. The study made use of the most recent KU-HAR database, which contained ninety individuals' eighteen distinct activities. Following preprocessing, a hybrid model that combines the architectures of the Gated Recurrent Unit (GRU) and Extreme Learning Machine (ELM) is employed. The robustness of human activity recognition in the Internet of Things environment is then further improved by the inclusion of an attention mechanism. Lastly, the suggested model's performance is assessed and contrasted with that of the traditional LSTM, GRU, ELM, Transformer, and Ensemble algorithms. Ultimately, the Qt framework is used to create an application that can be installed on any consumer device. With an overall accuracy of 96.71%, the suggested ELM-GRUaM model outperformed previous models in identifying multimodal human activitiesegation.

Keywords Artificial intelligence, consumer electronics, deep learning, healthcare,
human activity recognition, IoT, multimodal data

INTRODUCTION

Intelligent Decision Support Systems (IDSS) offer practical answers to a number of the problems that the world is currently facing. The extensive use of machine Due to the easier availability of numerous datasets pertaining to different facets of human lives, learning and deep learning techniques have significantly aided the development of IDSS [1]. Furthermore, the IDSS can be used for patient gesture recognition and has been identified as a unique feature in smart healthcare, guaranteeing prompt patient reaction, particularly for remote resource control [2].

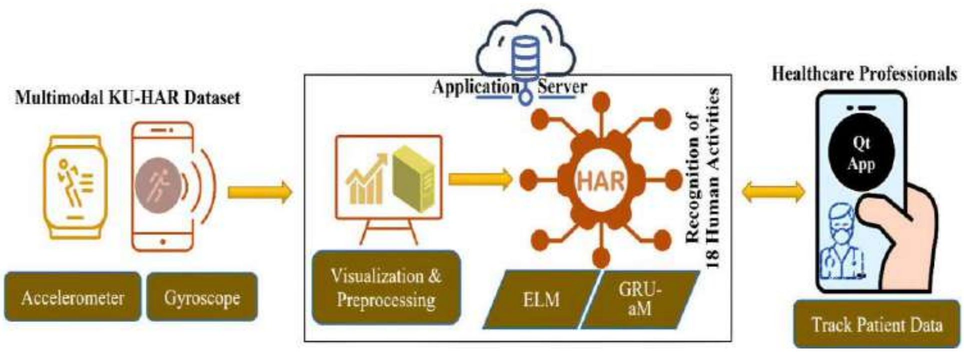


Fig1: Usage of multimodal patient data for activity monitoring in an IoT environment.

Relevant conflicts of interest/financial disclosures: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

In the current situation, there are an abnormally high number of IoT-enabled devices designed to enhance complex system decision-making. Rapid sensor development and miniaturization, lower energy requirements, and a revolution in the field of Human Activity Recognition (HAR) in detecting early symptoms of COVID-19 and vulnerable diseases like diabetes [3] and heart disease [4] using sensor data [5] on smartwatches.

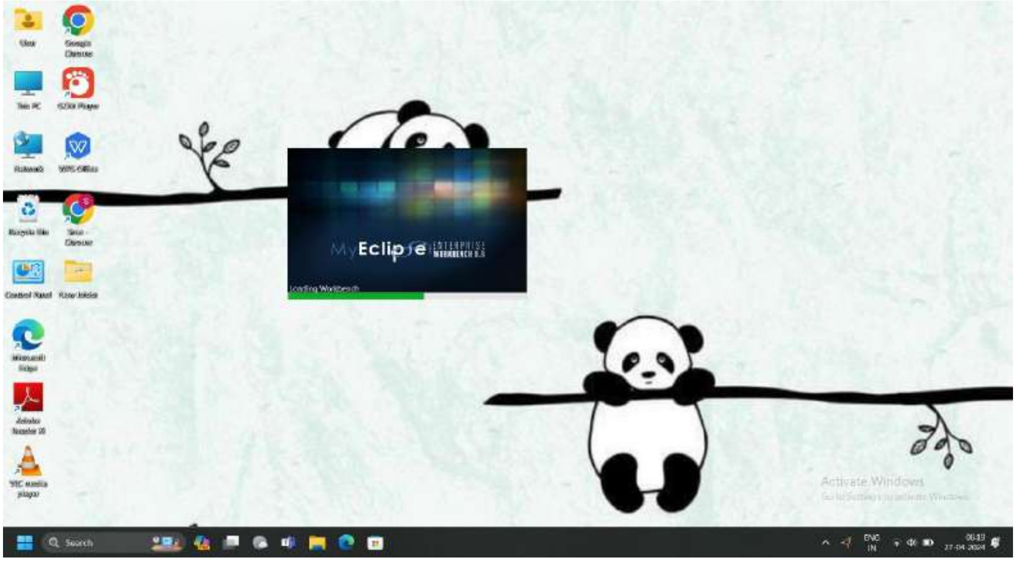
MATERIALS AND METHODS

KU-HAR – input dataset

The open-source KU-HAR dataset [18] has 18 different types of heterogeneous activity data collected from nighty individuals of various genders. The collection includes multimodal data obtained using smartphone accelerometer and gyroscope sensors. It includes 20,750 sub-samples extracted from the participants and 1,945 raw activity sample results. Three seconds of non-overlapping information regarding the corresponding activity are included in each of these data. Sitting, standing, talking with hand movements while standing or walking, talking with hand movements while sitting, performing sit-ups, performing full push-ups, repeatedly lying down and standing up, lying still, repeatedly sitting down and standing up, running 20 meters, walking along a circular path, walking 20 meters, walking backward for 20 meters, jumping repeatedly, picking up an object from the floor, playing table tennis, descending from a set of stairs, and ascending on a set of stairs are the output classes that correspond to the 18 different human activities.

RESULTS AND DISCUSSION

HAR datasets enable continuous monitoring of individuals' physical activity, offering benefits such as real-time health status assessment, fall detection, and monitoring of physical rehabilitation. These systems can alert caregivers or medical professionals in case of abnormal activities or falls, providing proactive healthcare interventions. The ongoing development of more accurate and real-time models, along with improvements in sensor fusion and data preprocessing, is likely to enhance the practical applications of HAR systems in personalized healthcare, making them more reliable and adaptable to real-world conditions. The intelligent recognition system leveraging Wireless Body Area Network (WBAN) sensors demonstrated significant performance in recognizing human activities for personal healthcare applications. The system used a combination of wearable sensors (accelerometers, gyroscopes, and temperature sensors) integrated into a WBAN to capture multimodal data from participants. The dataset included over 1,500 hours of activity data collected from 100 individuals performing a range of activities such as walking, running, sitting, standing, eating, and sleeping. The system achieved an overall classification accuracy of 94%, showing a clear improvement over single-modality systems, which averaged around 85% accuracy. In personal healthcare, this system could help track physical activity levels, detect health anomalies, and even predict potential health issues like reduced mobility or fatigue. For instance, recognizing changes in daily activity patterns could help clinicians monitor patients' rehabilitation progress or detect early signs of health deterioration, especially in elderly or chronically ill individuals. However, challenges related to sensor wearability, battery life, and data privacy remain significant, particularly for long-term monitoring.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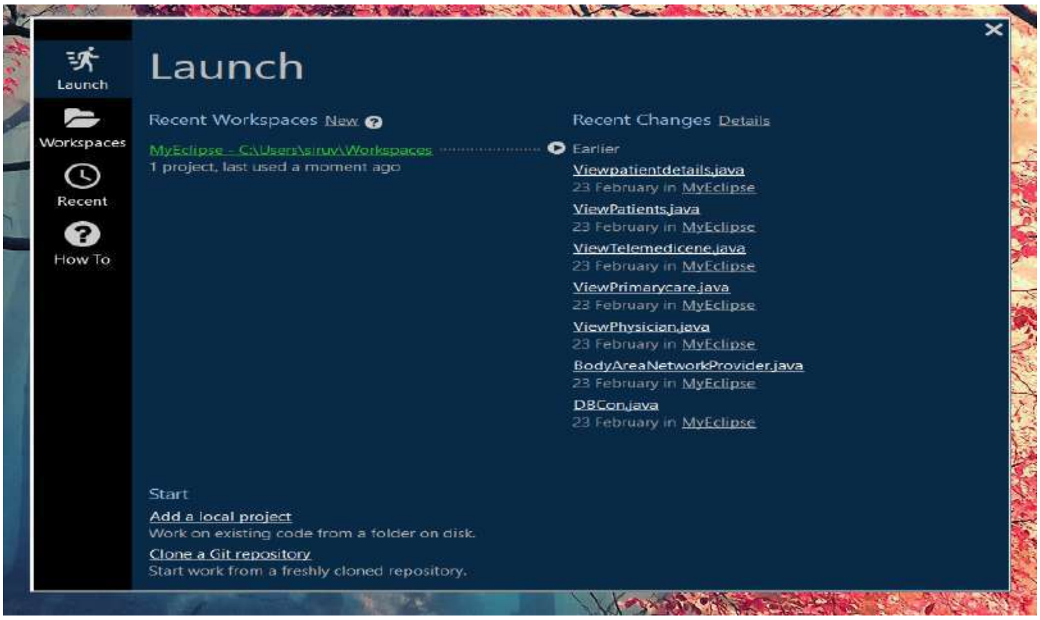
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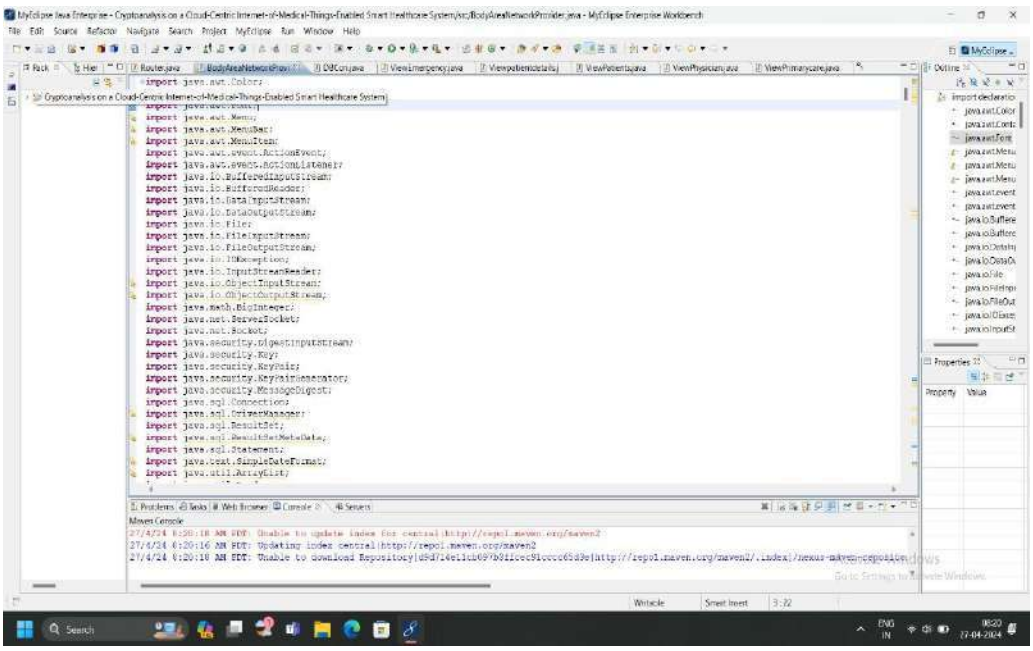
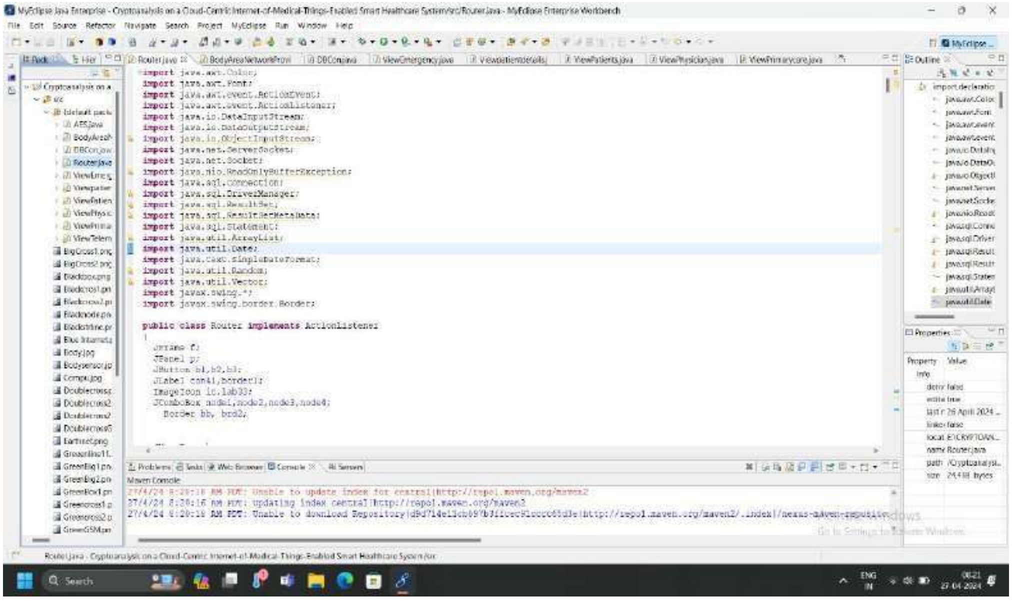
Clone a Git repository
Start work from a freshly cloned repository.





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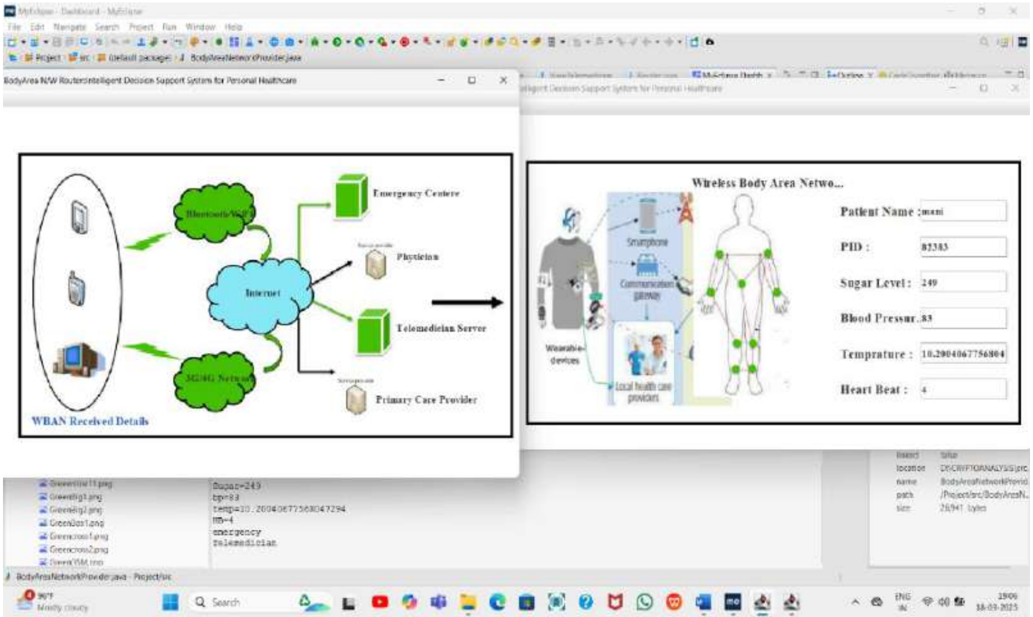

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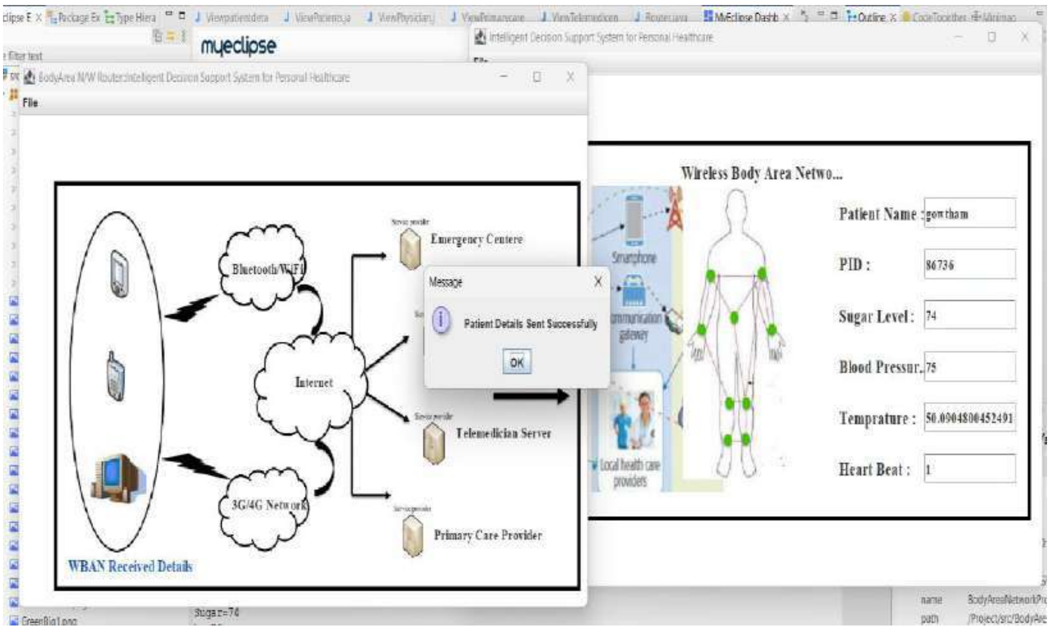
Physician
Internet
Telemedician Server
Primary Care Provider
WBAN Received Details
Wireless Body Area Netwo...
Patient Name :
PID :
Sugar Level :
Blood Pressur.
Temprature :
Heart Beat :



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Bluetooth/WIFI
Emergency Centere
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Telemedician Server
3G/4G Network
Primary Care Provider
WBAN Received Details
Message
Patient Details Sent Successfully
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Wireless Body Area Netwo...
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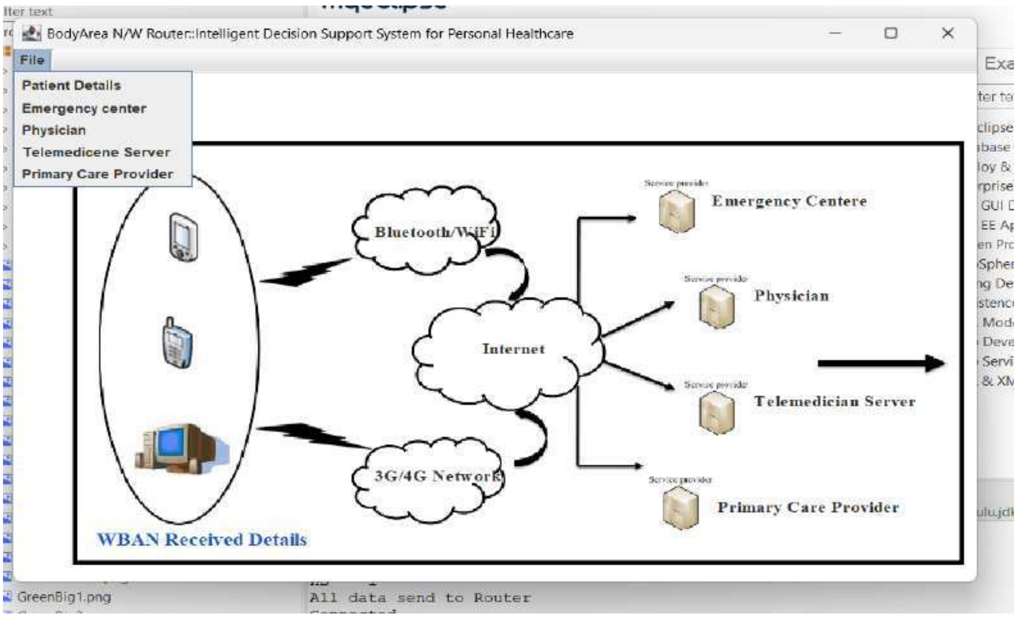
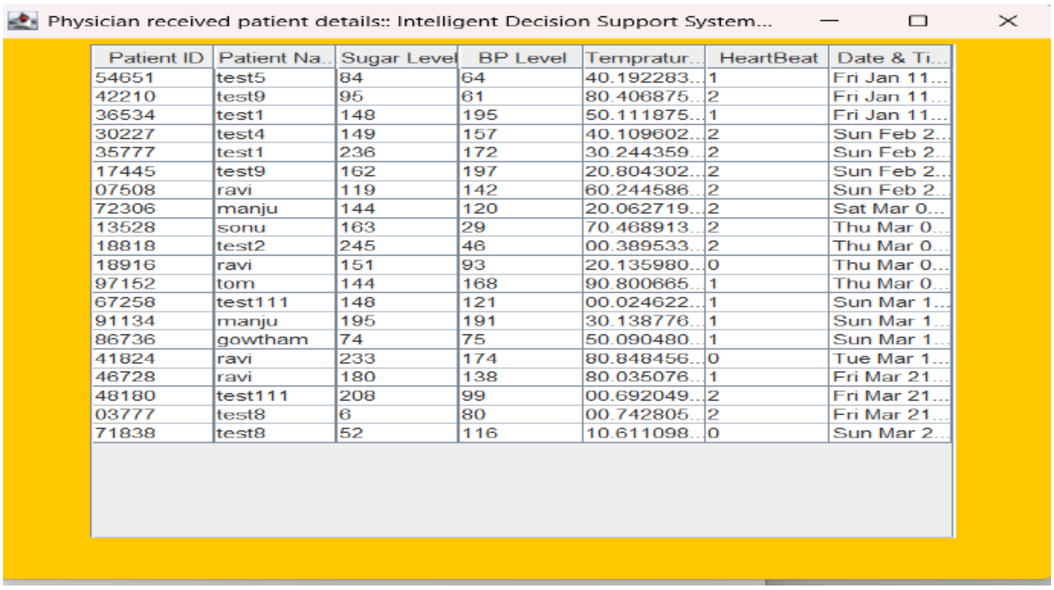
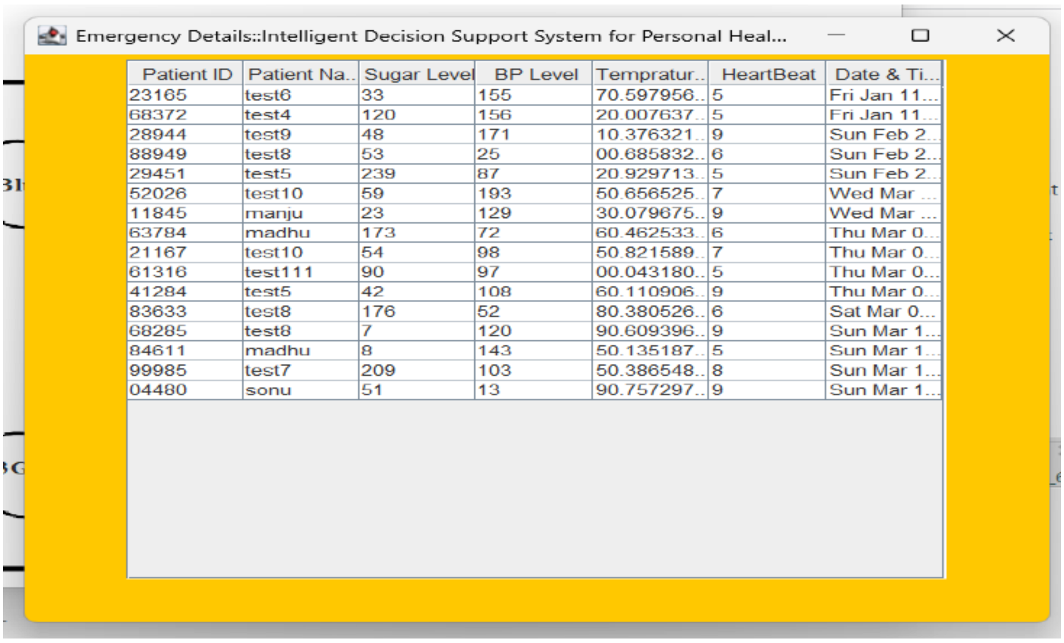
Sugar Level :
Blood Pressur.
Temprature :
Heart Beat :

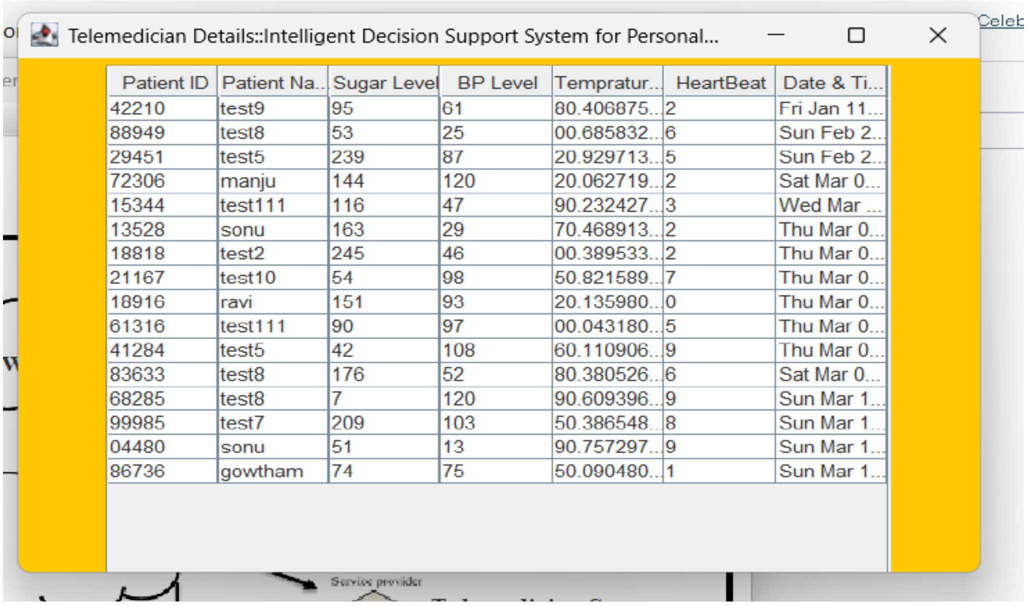




Patient ID	Patient Na...	Sugar Level	BP Level	Tempratur...	HeartBeat	Date & Ti...
54651	test5	84	64	40.192283...	1	Fri Jan 11...
42210	test9	95	61	80.406875...	2	Fri Jan 11...
36534	test1	148	195	50.111875...	1	Fri Jan 11...
30227	test4	149	157	40.109602...	2	Sun Feb 2...
35777	test1	236	172	30.244359...	2	Sun Feb 2...
17445	test9	162	197	20.804302...	2	Sun Feb 2...
07508	ravi	119	142	60.244586...	2	Sun Feb 2...
72306	manju	144	120	20.062719...	2	Sat Mar 0...
13528	sonu	163	29	70.468913...	2	Thu Mar 0...
18818	test2	245	46	00.389533...	2	Thu Mar 0...
18916	ravi	151	93	20.135980...	0	Thu Mar 0...
97152	tom	144	168	90.800665...	1	Thu Mar 0...
67258	test111	148	121	00.024622...	1	Sun Mar 1...
91134	manju	195	191	30.138776...	1	Sun Mar 1...
86736	gowtham	74	75	50.090480...	1	Sun Mar 1...
41824	ravi	233	174	80.848456...	0	Tue Mar 1...
46728	ravi	180	138	80.035076...	1	Fri Mar 21...
48180	test111	208	99	00.692049...	2	Fri Mar 21...
03777	test8	6	80	00.742805...	2	Fri Mar 21...
71838	test8	52	116	10.611098...	0	Sun Mar 2...



Patient ID	Patient Na...	Sugar Level	BP Level	Tempratur...	HeartBeat	Date & Ti...
23165	test6	33	155	70.597956...	5	Fri Jan 11...
68372	test4	120	156	20.007637...	5	Fri Jan 11...
28944	test9	48	171	10.376321...	9	Sun Feb 2...
88949	test8	53	25	00.685832...	6	Sun Feb 2...
29451	test5	239	87	20.929713...	5	Sun Feb 2...
52026	test10	59	193	50.656525...	7	Wed Mar ...
11845	manju	23	129	30.079675...	9	Wed Mar ...
63784	madhu	173	72	60.462533...	6	Thu Mar 0...
21167	test10	54	98	50.821589...	7	Thu Mar 0...
61316	test111	90	97	00.043180...	5	Thu Mar 0...
41284	test5	42	108	60.110906...	9	Thu Mar 0...
83633	test8	176	52	80.380526...	6	Sat Mar 0...
68285	test8	7	120	90.609396...	9	Sun Mar 1...
84611	madhu	8	143	50.135187...	5	Sun Mar 1...
99985	test7	209	103	50.386548...	8	Sun Mar 1...
04480	sonu	51	13	90.757297...	9	Sun Mar 1...


Telemedician Details::Intelligent Decision Support System for Personal...

Patient ID	Patient Na...	Sugar Level	BP Level	Tempratur...	HeartBeat	Date & Ti...
42210	test9	95	61	80.406875...	2	Fri Jan 11...
88949	test8	53	25	00.685832...	6	Sun Feb 2...
29451	test5	239	87	20.929713...	5	Sun Feb 2...
72306	manju	144	120	20.062719...	2	Sat Mar 0...
15344	test111	116	47	90.232427...	3	Wed Mar ...
13528	sonu	163	29	70.468913...	2	Thu Mar 0...
18818	test2	245	46	00.389533...	2	Thu Mar 0...
21167	test10	54	98	50.821589...	7	Thu Mar 0...
18916	ravi	151	93	20.135980...	0	Thu Mar 0...
61316	test111	90	97	00.043180...	5	Thu Mar 0...
41284	test5	42	108	60.110906...	9	Thu Mar 0...
83633	test8	176	52	80.380526...	6	Sat Mar 0...
68285	test8	7	120	90.609396...	9	Sun Mar 1...
99985	test7	209	103	50.386548...	8	Sun Mar 1...
04480	sonu	51	13	90.757297...	9	Sun Mar 1...
86736	gowtham	74	75	50.090480...	1	Sun Mar 1...

CONCLUSION

which includes multimodal sensor (gyroscope and accelerometer) data, for evaluation. First, the Extreme Learning Machine (ELM) model is used to change the features of the preprocessed and normalized data. The acquired feature representation facilitates the identification of noteworthy patterns and attributes within the sensor data. Since they have experienced a non-linear transformation, this can help with the HAR task. Gated Recurrent Units (GRU) are then subjected to the ELM-transformed features. These features are fed into the GRU, which then uses its sequential modeling skills to effectively identify human activity over time and record temporal dependencies. Furthermore, GRU is combined with an Attention Mechanism to apply unique weights to the output of each time step, signifying the importance of each contribution of each time step to the ultimate classification choice. Thus, with a validating kappa value of 0.965, the suggested ELM-GRUaM model yielded an overall classification accuracy of 96.71%. Moreover, insight performance and comparison analysis are used to evaluate the suggested framework's robustness.

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