Digital Twin-assisted Blockchain-inspired irregular event analysis for eldercare

Department of Computer Science and Engineering
박희지

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서울과학기술대학교
SEOULTECH
UCSLAB
Ubiquitous Computing & Security Laboratory

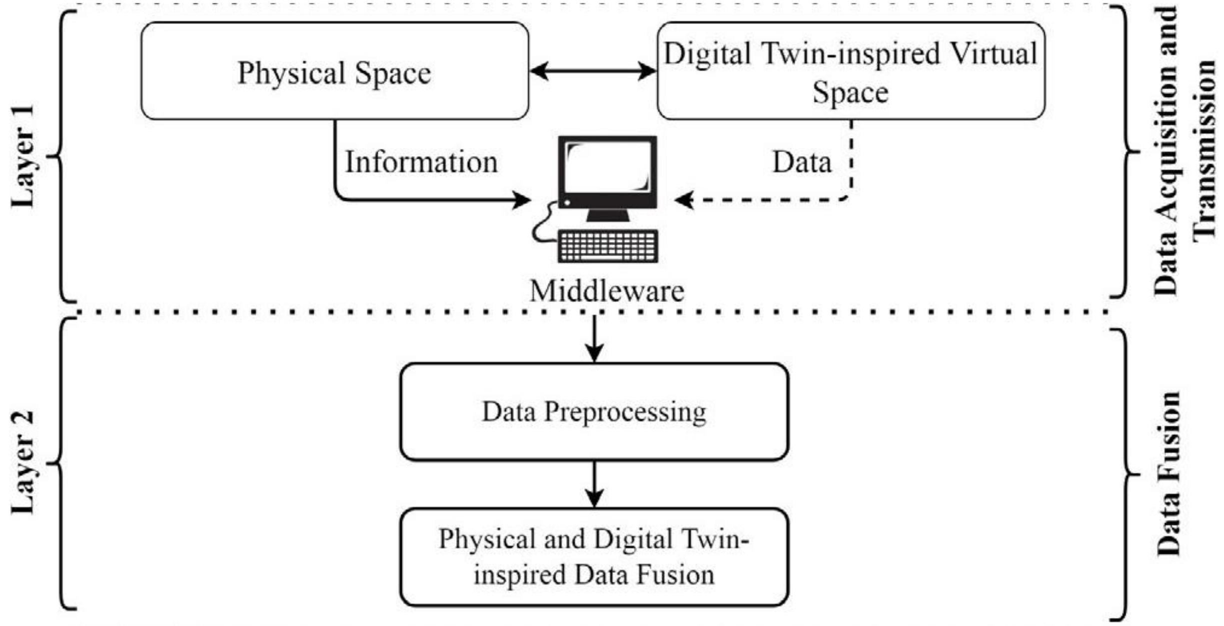
CONTENTS

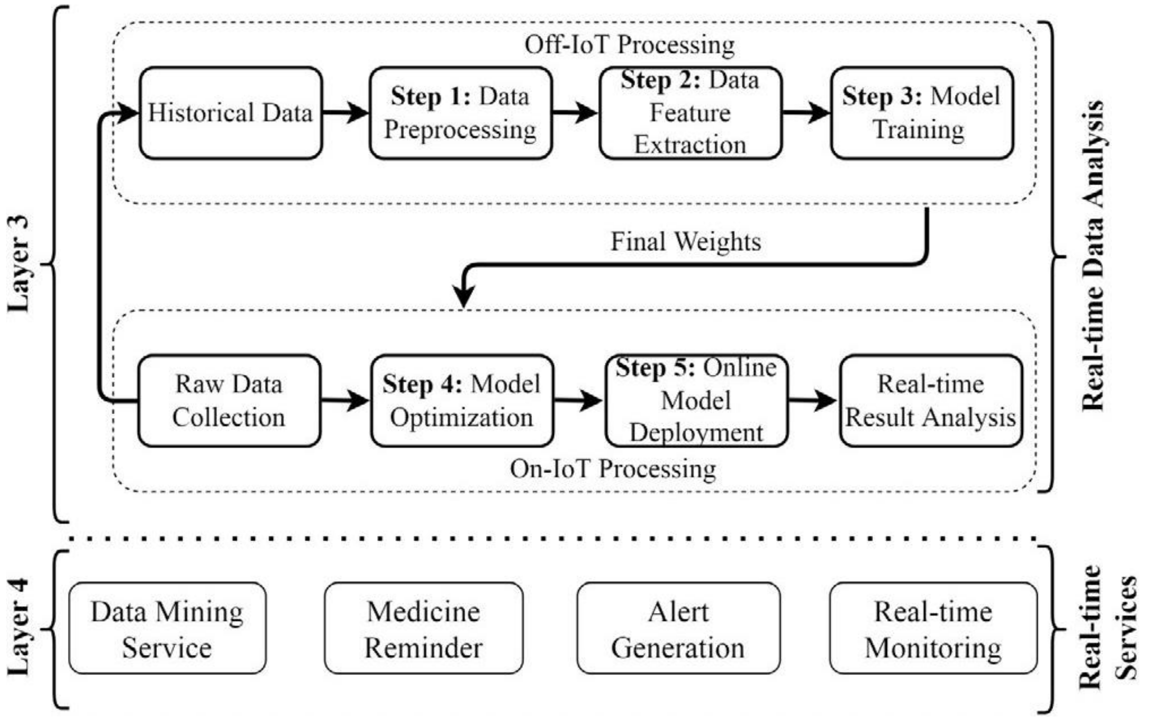
3. Digital Twin and Blockchain-inspired proposed solution

3.4. Real-time services

The process of traditional smart healthcare is always completed in four levels

1. Data acquisition
2. Data analysis
3. Result evaluation
4. Relevant decision making





3. Digital Twin and Blockchain-inspired proposed solution

3.4. Real-time services

- This layer provide a real-time health-assistive environment with blockchain-assisted personal health data management.
- As the upper layer is responsible to predict any irregular physical event, the present solution follows the process of severity analysis by generating an alarm to the caretaker or medical representative in real time.
- The complete process of severity analysis by generating a real-time alert is presented in Algorithm 2.

Algorithm 2 An algorithm of time-sensitive alert generation

Require: $Event_i$
Ensure: Alert
  if $Event_i \leq$ Threshold **then**
    Alert = High
  else
    for i = 1 to m **do**
      Calculate $\delta i = Event_i - Event_{i+1}$
    end for
  end if
  if $\delta i \leq$ Threshold **then**
    Alert = High
  else
    Alert = Low
  end if

3. Digital Twin and Blockchain-inspired proposed solution

3.4. Real-time services

Data block generation

- Once the proposed solution determines the irregular event, the data related to the predicted event is sent to the blockchain.
- The concept of Data Aggregation (DA) is responsible to bundled the number of transactions to form a single block [36–38].
- As we are following a consortium blockchain, the process of verification is not required.
- The utilization of the blockchain in the proposed solution is having the objective to pro- vide clinical assistance to elder individuals in the case of severity determination.
- Moreover, each stakeholder such as clinical officials, medication providers, and resource supervisors is part of the process that can utilize the data of this blockchain.
- In this manner, blocks Bi are created intermittently in the proposed solution and illustrated in Fig. 5.

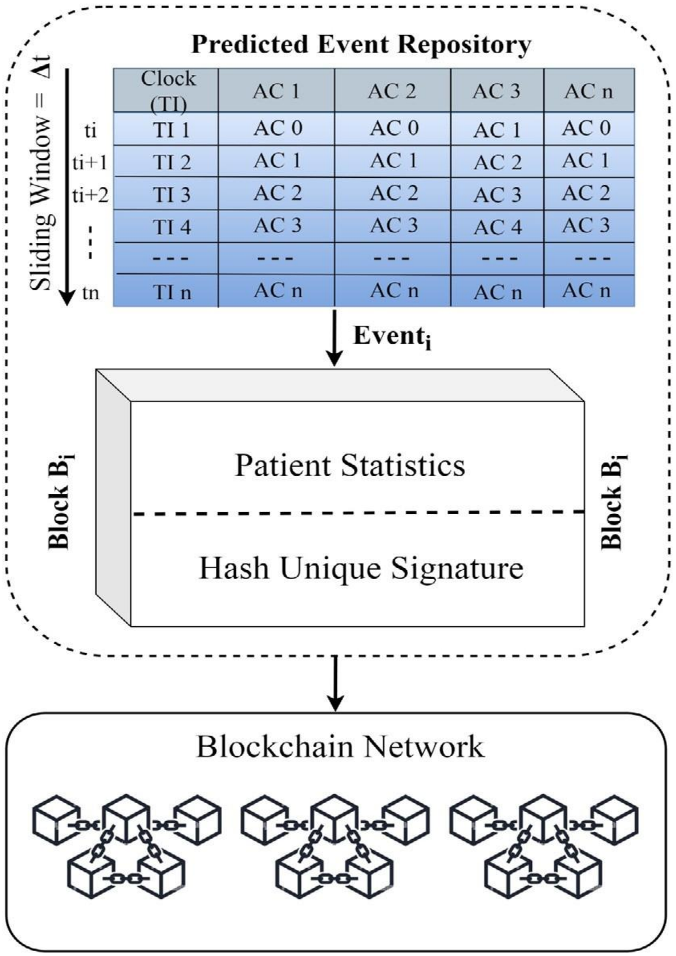


Fig 5. The systematic flow of single block generation

3. Digital Twin and Blockchain-inspired proposed solution

3.4. Real-time services

Consensus and chaining of blocks

- The RBFT gives the necessary advantages of security, reliability, decentralization, and transaction finality with less delay and high throughput. In the proposed solution, the decision based on consensus is achieved by executing customized RBFT.
- After the generation of block Bi, the validator broadcasts the block to the network to create a blockchain.
- The individuals with respect to the blockchain net- work approve the transaction exclusively and sign the header of that approved block.
- In this manner, the identity-based signatures done by the individuals on the blocks are considered votes [41].
- The utilization of the consortium blockchain and this vote-based system helps to achieve high throughput and low rate of latency that helps to prevent 51% of attacks.

Algorithm 3 An algorithm of Customized RBFT and Block Chaining

Require: B_i
Ensure: Consensus decision
  Transaction verification
  for Peer=i to N **do**
    Calculate Signature B_i
    j++
  end for
  if j $\geq \mu$ **then**
    NTP server-based request generation
    Perform timestamping and hashing
    Consensus = true
    Process of blockchain updation = True
  else
    Wait for definite time event ΔT
  end if
  Return consensus

Algorithm 3. which represents the complete process of consensus, N defines the number of individuals belonging to the consortium and the special symbol μ defines the signature done by the individuals on the block Bi for the verification

4. Performance evaluation

- The detail with respect to the performance of the proposed solution for event recognition, model training and testing validation, rate of latency, and data processing cost are provided in this section.
- The analysis has been done by utilizing Python, Sklearn library, Tensorflow, and Keras. Moreover, different libraries such as Numpy, Pandas, and Matplotlib are utilized for data prepro- cessing and result calculation. Furthermore, RBFT is implemented in C++ programming language by integrating with the Python framework.
- As the concept of blockchain with DT in the domain of irregular physical event determination is a novel exploration, therefore, the comparative is inconsequential. The experimental specifications, performance metrics, and results are discussed in the following sub-sections as follows:

    1. Movement recognition performance analysis
    2. Model training and testing accuracy validation
    3. Rate of latency evaluation
    4. Data processing cost measurement

4. Performance evaluation

4.1. Movement prediction performance analysis

The performance of the proposed movement prediction methodology is validated as follows:

4.1.1. Selection of optimal hyperparameters

4.1.2. Optimum selection of event window

4.1.3. Overall event determination accuracy

4.1.1. Selection of optimal hyperparameters

- As deep learning is following the concept of Greedy Tuning, different hyperparame- ters are selected and applied to the proposed approach to decide the most reasonable configuration for event determination.
- The effective features have been extracted from the data windows by varying the number of convolutional layers and pooling layers with different sizes of filters and feature maps.
- A total of 4 convolutional layers are designed by incorporating different parameters such as learning rate, padding, and max-pooling to perform the process of feature extraction.

4. Performance evaluation

4.1. Movement prediction performance analysis

4.1.1. Selection of optimal hyperparameters

Number of layers

- The optimal hyperparameters related to the number of convolutional layers are presented in Fig. 6. From the calculated outcomes, it can be analyzed that significant and consistent training accuracy has been achieved by including the first three layers.
- However, after including layer 4, a loss gap has been observed between layer 4 and layer 3. The proposed model has started to lose its accuracy after including layer 4.
- In this manner, a total of three convolutional layers are considered optimum to extract the features from the data and to predict the singular event efficiently.

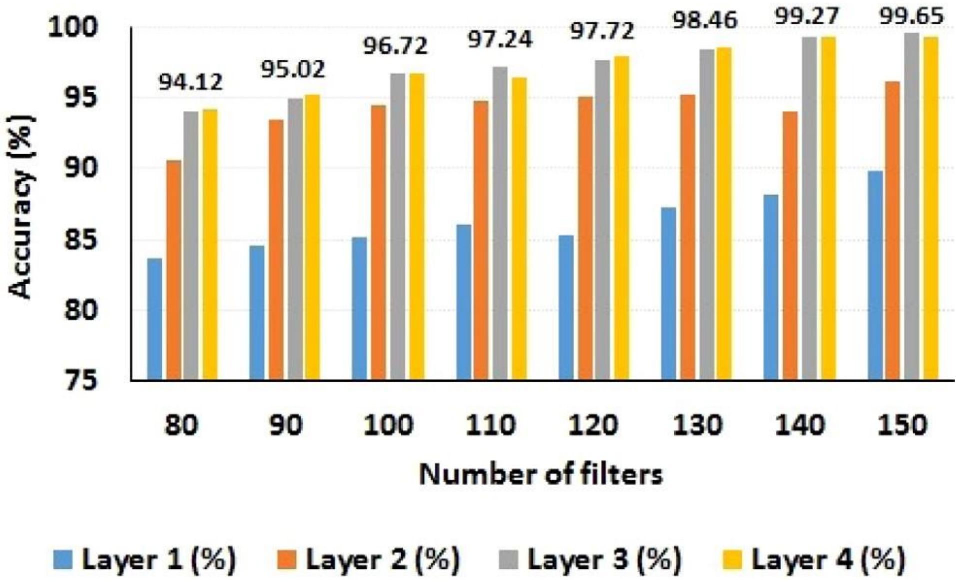


Fig. 6. The selection of an optimal number of CNN layers.

4. Performance evaluation

4.1. Movement prediction performance analysis

4.1.1. Selection of optimal hyperparameters

Number of feature maps and size

- For CNN layers, a different set of feature maps such as 90, 110, 130, and 150 are used to extract features and the calculated outcomes are illustrated in Fig. 7.
- By using the above-mentioned features maps, the proposed solution has achieved the accuracy of 83.88%, 88.97%, 90.67%, and 90.44% respectively and the calculated variability is displayed in Fig. 7. From the calculated outcomes, it can be observed that the proposed solution has achieved the maximum accuracy of 90.67% by applying 130 feature maps.
- Moreover, minimal degradation has been observed after applying 150 feature maps.
- After deciding the optimal number of feature maps, the feature extraction accuracy is also evaluated by updating the size from 1 × 5 to 1 × 10 and presented in Fig. 8. The calculated outcomes show that the channel size from 1 × 8 to 1 × 10 gives the optimal accuracy on the test dataset.

4. Performance evaluation

4.1. Movement prediction performance analysis

4.1.1. Selection of optimal hyperparameters

Number of feature maps and size

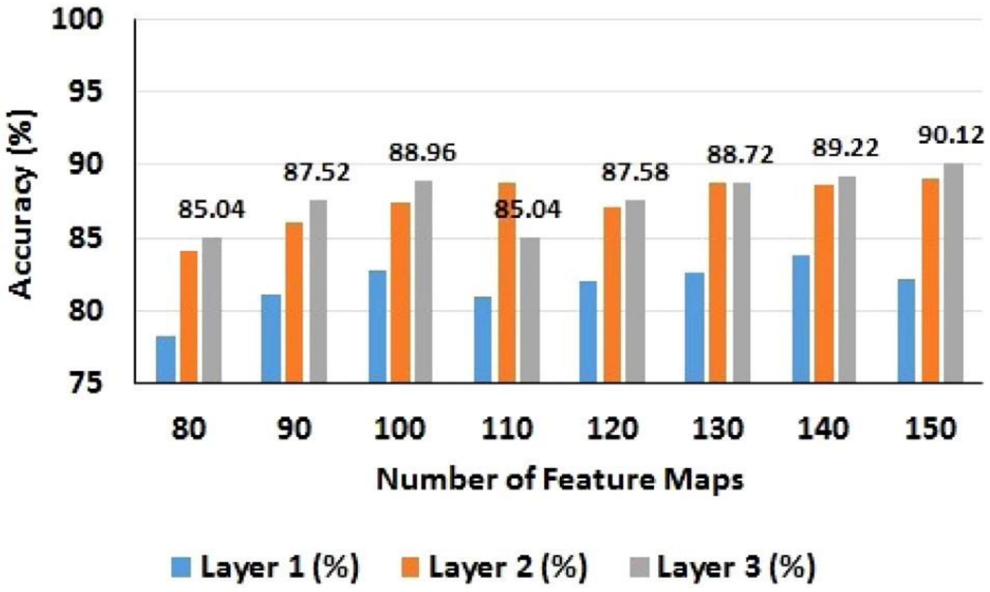


Fig. 7. The selection of an optimal number of feature maps

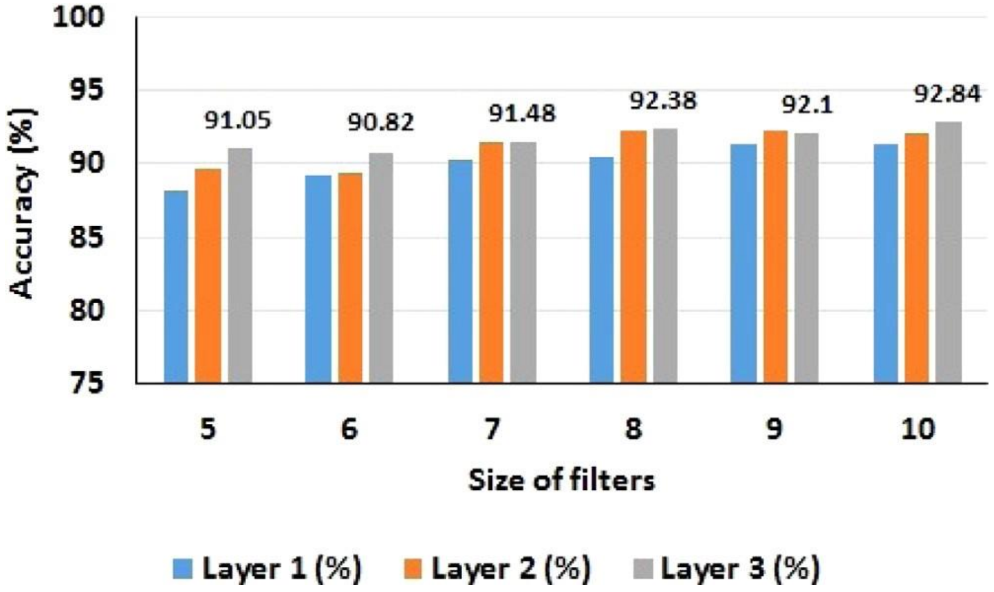


Fig. 8. The selection of the optimal size of feature maps.

4. Performance evaluation

4.1. Movement prediction performance analysis

4.1.1. Selection of optimal hyperparameters

Size of pooling layers

Unlike the filter size, the size of pooling does not influence the performance of the CNN model as illustrated in Fig. 9. Over the different number of iterations, a pooling size of 1 × 3 is chosen as adequate to operate pooling.

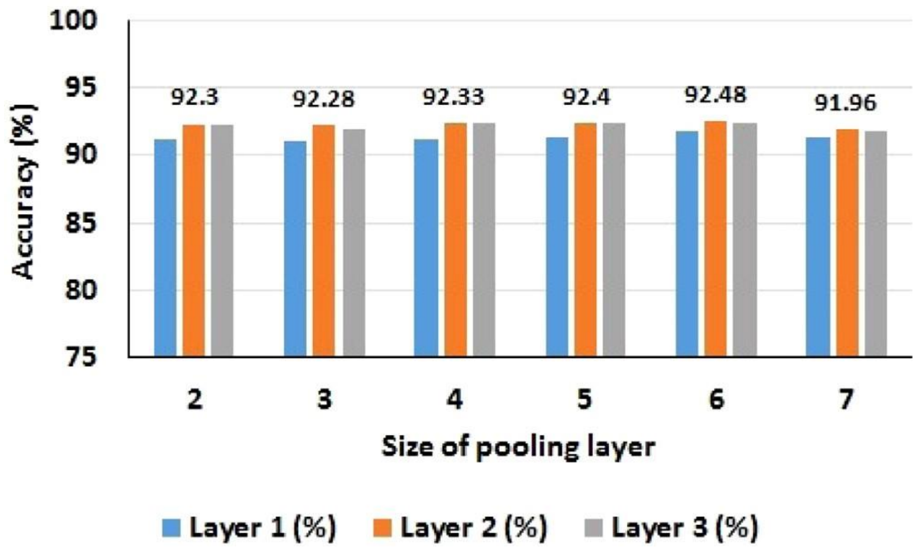


Fig. 9. The selection of the optimal size of feature maps.

4. Performance evaluation

4.1. Movement prediction performance analysis

4.1.1. Selection of optimal hyperparameters

Finalized hyperparameters

- After selecting the optimal size of the pooling layer, the best hyperparameters for the CNN model are listed as Number of CNN Layers = 3, Number of Feature Maps = 130, Optimal Size of Feature Map = 1 9, and Optimal Size of Pooling Layer = 1 3, and the proposed solution has achieved the maximum accuracy of 90.68% on test samples.
- Moreover, it has been realized that the model can achieve an accuracy of 91.71% of the accuracy after adding 2 fully connected layers with 1024 nodes.

Number of GRU units

- To deal with the sequentiality in the captured event, the last layers of the proposed CNN model are re-placed with the bidirectional GRU units.
- To achieve the maximum event determination accuracy, a different number of GRU cells have been added to the GRU unit varying from 20 cells to 140 cells and the calculated outcomes are presented in Fig. 10. From the calculated outcomes it can be observed that the GRU model with 64 cells has achieved the maximum accuracy of 95.29%.

4. Performance evaluation

4.1. Movement prediction performance analysis

4.1.2. Optimum selection of event window

- The event determination efficiency of an individual is directly dependent upon the length of the event and the buffering capability of the server.
- Table 4 represents that the window size larger than 0.75s can be a reason for more delay in the result generation and the proposed solution is losing the strength of event determination. In this manner, it can be analyzed that the window size of fewer than 0.75 s gives more data processing efficiency with more accuracy and a better throughput rate.
- Moreover, the proposed model is generating the optimal outcome with an accuracy of 94.24% by utilizing the data with the window size of 0.50 s as compared to the other selected sizes.
- Therefore, all the outcomes are calculated on 0.50 s of window size.

Table 4
Analysis of accuracy with respect to window size.

Sr. no.	Event window size (In s)	Accuracy (%)
1.	0.25	86.94
2.	0.50	94.24
3.	0.75	91.68
4.	1.00	88.37

4. Performance evaluation

4.1. Movement prediction performance analysis

4.1.3. Overall event determination accuracy

- To validate the performance of the proposed solution, different State-of-The-Art (SoTA) solutions like Electrophoretic Mobility Shift Assay, Hidden Markov Model, and Deep Belief Network have been implemented and the calculated outcomes are compared with the proposed solution.
- The performance is analyzed by calculating different performance matrices such as Precision, Recall, and F-measure.
- The event determination outcomes with respect to the 10 physical activities considered in the proposed study are presented in Tables 5, 6, and 7.
- From the calculated outcomes, it can be analyzed that the proposed approach has achieved the maximum precision of 94.24% as compared to the EMSA, HMM, and DBN with the accuracy of 88.51%, 81.07%, and 83.56%, respectively.

4. Performance evaluation

4.1. Movement prediction performance analysis

4.1.3. Overall event determination accuracy

Table 5
Precision classification scores for each activity.

Activities	SoTA 1 (%)	SoTA 2 (%)	SoTA 3 (%)	Proposed system (%)
Activity 1	94.24	88.34	89.62	99.92
Activity 2	77.52	68.71	70.02	88.24
Activity 3	77.39	71.23	73.58	85.26
Activity 4	96.48	85.49	87.23	98.74
Activity 5	89.12	83.65	80.24	87.42
Activity 6	92.23	87.21	89.62	96.84
Activity 7	95.02	87.82	91.12	98.82
Activity 8	90.42	80.12	84.28	88.57
Activity 9	89.62	83.24	88.23	98.26
Activity 10	83.02	75.92	77.24	100
MEAN	**88.51**	**81.07**	**83.56**	**94.24**

Electrophoretic Mobility Shift Assay: SoTA 1, Hidden Markov Model: SoTA 2, Deep Belief Network: SoTA 3, Sitting and relaxing: Activity 1, Standing still: Activity 2, Walking: Activity 3, Lying down: Activity 4, Waist bends forward: Activity 5, Knees movement: Activity 6, Frontal elevation of arms: Activity 7, Jogging: Activity 8, Falling: Activity 9, Running: Activity 10.

Table 6
Recall classification scores for each activity.

Activities	SoTA 1 (%)	SoTA 2 (%)	SoTA 3 (%)	Proposed system (%)
Activity 1	92.27	83.24	82.36	92.23
Activity 2	72.42	62.36	65.24	86.54
Activity 3	75.74	68.24	71.24	83.88
Activity 4	92.25	81.24	83.25	93.54
Activity 5	89.12	80.45	78.26	85.24
Activity 6	88.25	81.68	84.57	92.38
Activity 7	90.54	78.46	81.06	95.67
Activity 8	84.36	77.85	82.51	82.57
Activity 9	85.72	80.23	84.02	92.65
Activity 10	80.52	70.69	75.67	89.52
MEAN	**85.12**	**76.28**	**78.48**	**89.58**

Electrophoretic Mobility Shift Assay: SoTA 1, Hidden Markov Model: SoTA 2, Deep Belief Network: SoTA 3, Sitting and relaxing: Activity 1, Standing still: Activity 2, Walking: Activity 3, Lying down: Activity 4, Waist bends forward: Activity 5, Knees movement: Activity 6, Frontal elevation of arms: Activity 7, Jogging: Activity 8, Falling: Activity 9, Running: Activity 10.

4. Performance evaluation

Table 7
F-measure classification scores for each activity.

Activities	SoTA 1 (%)	SoTA 2 (%)	SoTA 3 (%)	Proposed system (%)
Activity 1	95.52	81.24	82.42	96.49
Activity 2	75.87	60.28	64.72	83.54
Activity 3	75.02	66.58	68.29	85.26
Activity 4	93.57	85.94	83.78	98.70
Activity 5	88.62	88.71	84.26	89.28
Activity 6	90.54	79.25	88.29	96.56
Activity 7	92.24	85.58	87.85	98.72
Activity 8	87.78	88.84	85.28	88.41
Activity 9	87.52	78.24	84.36	90.65
Activity 10	82.25	68.26	78.26	87.54
MEAN	**86.89**	**78.52**	**80.94**	**91.85**

Electrophoretic Mobility Shift Assay: SoTA 1, Hidden Markov Model: SoTA 2, Deep Belief Network: SoTA 3, Sitting and relaxing: Activity 1, Standing still: Activity 2, Walking: Activity 3, Lying down: Activity 4, Waist bends forward: Activity 5, Knees movement: Activity 6, Frontal elevation of arms: Activity 7, Jogging: Activity 8, Falling: Activity 9, Running: Activity 10.

-Similar event determination performance has been reported by the proposed approach for Recall and F-measure by achieving the accuracy of 89.58% and 91.85%, respectively which is as higher compared to the EMSA, HMM, and DBN. In this manner, the calculated outcomes show the viability of the proposed solution for sequential physical event determination as compared to the state-of-the-art approaches.

-To define the overall event determination performance based on the activity performed by the individual and to calculate the misclassification, a confusion matrix is calculated and presented in Table 8).

4. Performance evaluation

4.1. Movement prediction performance analysis

4.1.3. Overall event determination accuracy

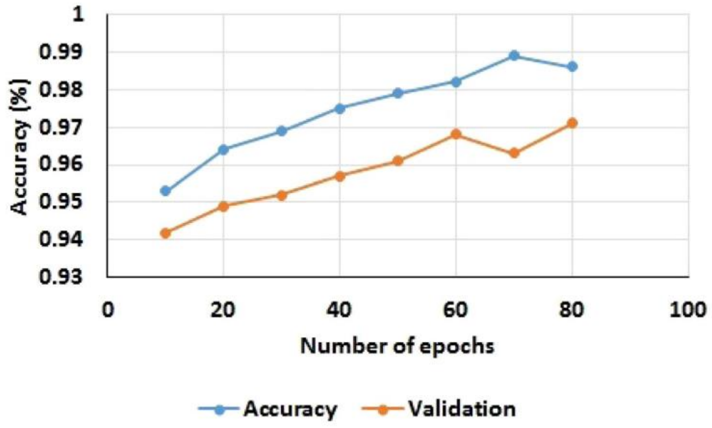
- To define the overall event determination performance based on the activity performed by the individual and to calculate the misclassification, a confusion matrix is calculated and presented in Table 8).
- From the confusion matrix, it can be easily determined the misclassification between physical events such as "running" and "Jogging". It became hard for the proposed approach to identify a differentiation between the event related to running activity and jogging activity because of the similar pattern.
- However, it can be analyzed that the misclassifications are not that critical and can deal with increasing the number of training and validation samples.

Table 8
Confusion matrix.

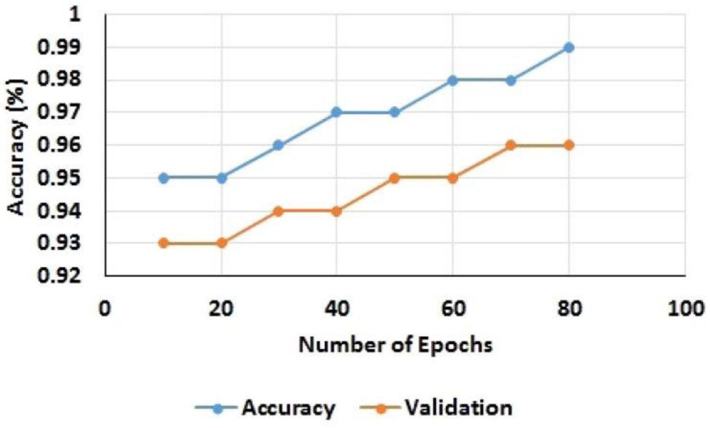
Activities	1 (%)	2 (%)	3 (%)	4 (%)	5 (%)	6 (%)	7 (%)	8 (%)	9 (%)	10 (%)
Activity 1	**100**	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Activity 2	0.0	**91.24**	0.0	0.0	0.0	0.0	0.0	2.8	0.0	0.0
Activity 3	0.0	0.0	**90.26**	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Activity 4	0.0	0.0	0.0	**98.74**	0.0	1.05	0.0	0.0	0.0	0.0
Activity 5	0.0	0.0	0.0	1.18	**88.42**	0.0	0.0	0.0	0.0	0.0
Activity 6	0.0	0.0	3.52	0.0	0.0	**95.84**	0.0	0.0	0.0	0.0
Activity 7	0.0	0.0	0.0	0.0	0.0	4.58	**97.82**	0.0	0.0	0.0
Activity 8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**90.57**	0.0	0.0
Activity 9	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**100**	0.0
Activity 10	0.0	0.0	0.0	0.0	0.0	0.0	0.0	7.8	0.0	**100**

4. Performance evaluation

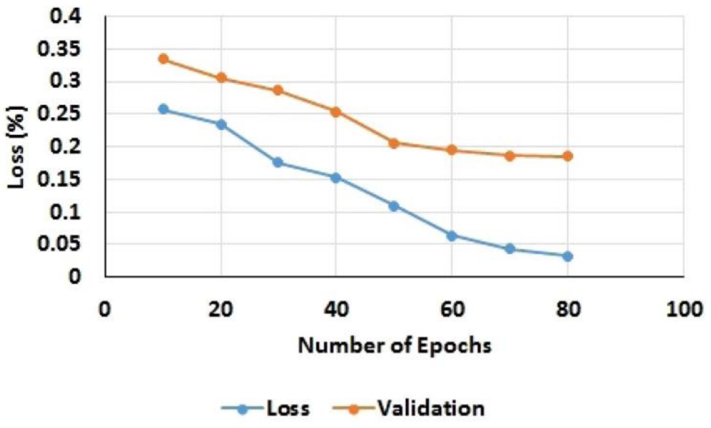
4.2. Model training and testing accuracy validation



(a) CNN training accuracy

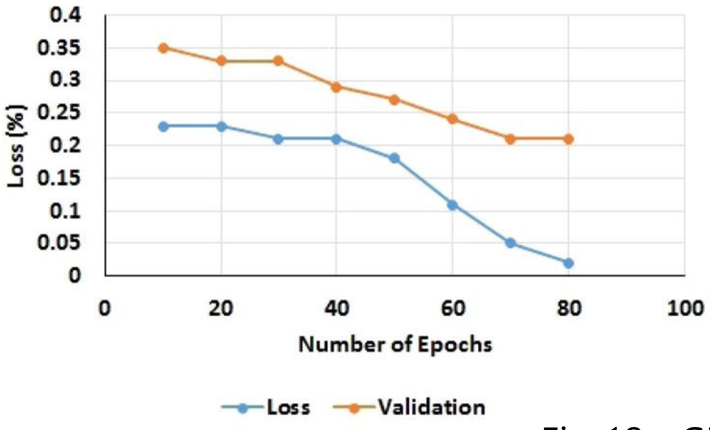


(a) GRU training accuracy



(b) CNN loss validation

Fig 11. CNN Performance Estimation.



(b) GRU loss validation

Fig 12. GRU Performance Estimation.

4. Performance evaluation

4.2. Model training and testing accuracy validation

- After analyzing the data processing capability of network net- works, a 3-layered CNN architecture is proposed and trained for a total of 80 epochs with a learning rate of 0.01.
- The training and validation performance of the proposed model with respect to CNN and GRU architecture is illustrated in Figs. 11 and 12.

- From the readings illustrated in Fig. 11, it can be analyzed that the optimal weights of the CNN model have been retrieved after 68 epochs by achieving the training accuracy of 0.98% with 0.033% loss.
- Moreover, the proposed architecture has achieved an accu- racy of 0.96% for validation with a loss of 0.14%.
- After finalizing the weights of the CNN model, the GRU network is also trained for 80 epochs with a learning rate of 0.01.
- Similar to CNN, the optimal weights for the GRU network have been achieved after 73 epochs by achieving the minimal loss of 0.033% and accuracy of 0.986% for training and that can be easily analyzed from Fig. 12.
- Similarly, the GRU network has achieved the validation accuracy of 0.971% with a loss of 0.143%.

4. Performance evaluation

4.3. Evaluation of rate of latency

- Rate of Latency (RoL) is considered as a difference between the time reported during the submission of a request and the time while getting the response from the receipt. Different RoLs are assessed as follows:

  4.3.1. RoL in Network

  4.3.2. RoL in Blockchain

4.3.1. RoL in Network

- In the domain of healthcare, it is imperative to calculate the latency of the network to transfer decisions in the form of alerts. Mathematically, RoL in Network is calculated as;

$$\text{RoL} = \text{Irregular event determination} - \text{Alert deliverance} \qquad (11)$$

- The rate of delay caused by sharing the common network with different applications in the Fog and Cloud layer is presented in Fig. 13. It has been analyzed that cloud-based healthcare frame- works deal with lesser bandwidth, increasing the congestion in the network, and calculating high round-trip as compared to the Fog-inspired healthcare frameworks. In this way, an average rate of delay in the network has been realized in the cloud-based solutions. On the other hand, less rate of delay has been calcu- lated in Fog-based healthcare solutions which is clearly illustrated in Fig. 13.

4. Performance evaluation

4.3. Evaluation of rate of latency

4.3.2. RoL in Blockchain

- To calculate the RoL for blockchain, three rates such as mini- mum, average, and maximum are calculated for all the generated blocks and peers with respect to a time event T . The RoL is also calculated by varying the number of peers and the calculated outcomes are illustrated in Table 9.
- The calculated RoL related to the blockchain is presented in Table 9. From the calculated outcomes, it has been observed that the rate of latency is increased while increasing the number of peers. In this manner, the average increasing factor with the increment of +1.55 is calculated and a similar increment with the rate of +1.32 is calculated for the minimum rate.
- It is imperative to make it clear that the utilization of signcryption and a light process of cryptography can be a reason for latency and internal calculation for block generation not participating. In this manner, it can be concluded that the increment of RoL is directly depen- dent upon the number of individuals involved in the process of blockchain.
- However, the calculated RoL makes the blockchain reasonable for healthcare applications.

4. Performance evaluation

4.3. Evaluation of rate of latency

Table 9
Blockchain-based transactional latency.

No. of peers	Success	Fail	Maximum latency	Minimum latency	Average latency
5	100%	0	0.90	0.32	0.66
10	100%	0	2.67	0.94	1.80
15	100%	0	5.33	2.77	4.01
20	100%	0	10.23	4.50	7.36

4.4. Data processing cost measurement

Table 10
Cost-estimation value.

Sr. no.	Type of cost	Cost value
1.	Computational cost	$O(N\ log_n)$
2.	Transaction cost	$O(N\text{-}1\ log_n)$

4. Performance evaluation

4.4. Data processing cost measurement

- It is imperative to measure the cost of the system to evalu- ate the decision-making efficiency of the proposed solution. In this manner, two types of costs such as transactional cost and computational cost are calculated. Computational cost defines the time taken by the system for decision-making with respect to the event captured at a specific time instance ΔT .
- The cost of a transaction defines the complexity related to the genera- tion and authentication of blocks in the network. The calculated complexities are illustrated in Table 10.
- The computational cost presented in Table 10 consisting the process of data generation, data preprocessing, and event deter- mination.
- On the other hand, the transactional cost is consisting the process of key and signcrypted message transmission with the cost of consensus.

5. Conclusion

- In this paper, a digital twin framework for elder individuals is proposed to determine the predict irregular events in their daily routine by utilizing the data acquisition and data processing efficiency of IoT and deep learning.
- The proposed solution can be considered a substantial solution for the particulars of the smart healthcare domain. Moreover, different issues related to digital twin technology such as sequential data analysis, data security, latency issues, and demand-based immediacy.
- The calculated outcomes demonstrate the efficacy of the proposed approach for irregular event determination by analyzing the cost and time complexity.
- However, one major limitation related to the digital twin is observed in the proposed study.
- As the digital twin is not a one-time training process, practising the process of looping is compulsory to optimize the ability of event determination. In this manner, the development of continuous improvement and self- adaption with respect to practical research in a digital twin is required.
- Moreover, the proposed approach can be generalized to other domains in future that can help to reduce the risk factor and improve the economic benefits.

* Opinion

Unlike The process of traditional smart healthcare, which takes place in the stages of Data acquisition, Data analysis, Result evaluation, and Revenant decision making, the proposed system uses the concept of digital twin to create virtual copies of individuals under observation and analyze all situations in real time.

I thought it would be good to apply digital twin to the paper related to the contest I am currently writing.

THANK YOU