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Preventing the Propagation of Influenza disease through Simulated Cluster-and Smartphone-Based Body Area Networks

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A B S T R A C T

Influenza, also known as "the flu," is a highly contagious viral infection of the respiratory tract. Symptoms include fever, cough, sore throat, muscle pains, and exhaustion, which can range from moderate to severe. Influenza is caused by influenza viruses, and there are many different strains, some of which may change each year. Influenza has affected various countries throughout the world and is increasingly emerging as a global public threat. Controlling this type of virus and reducing its spread among the global population is difficult due to its multiple modes of transmission which include direct contact, droplet, and possible aerosol transmissions, as well as various factors such as increased population density, closer social contact, and interactions. Other elements that make influenza control difficult include the identification of regular variations which have frequently caused a slew of difficulties as more people become susceptible to illness. Influenza vaccinations are ineffective since even those who have been vaccinated are vulnerable to attack and can contaminate others. To detect the presence of this virus, the healthcare sector, in partnership with information technology partners, developed numerous influenza-presence detection devices utilizing various algorithms which played critical roles in its containment. In this study, we take a different approach. We use simulations to develop a Cluster-Based Influenza Control Mechanism using the Smartphone-Based Body Area Networks (CCISBAN) protocol. This mechanism simulates a body sensor that can detect influenza and its variants on people's body temperature (BT), oxygen saturation (OS), blood pressure (BP), and respiratory rate (RR) on their smartphones. This unique technique splits populations into various clusters based on the severity of their vital signs; it is a computationally efficient approach, and its sub-module allows for an effective cluster-based quarantine strategy. The biosensor detects the presence of the virus and its variations even in trace amounts. This proposed method is a trustworthy mechanism that can deliver information to people and advise them to do a medical Influenza test before self-isolating or being isolated by authorities. This successful prototype can be further developed and tested on real social interaction networks in hardware by IT geeks working with health-care organizations.

Keywords: *Body Area networks, epidemic control, smartphone, clustering.*

1. Introduction

An epidemic disease is the widespread presence of an infectious disease in a community at a certain time. It denotes the rapid spread of a disease among a significant number of people within a certain population and timeframe. Epidemic control becomes more difficult as population density increases, as does tighter social contact and interaction. Traditional offline epidemic control methods (e.g., using medical surveys or medical records) and model-based approaches are ineffective because they cannot collect health data and social contact information at the same time or make impractical statistical assumptions about the dynamics of social contact networks. Furthermore, due to the high computational complexity, it is difficult to identify ideal sets of people to confine in order to control the spread of epidemics in huge populations. Unlike previous techniques, this research proposes a unique cluster-based pandemic control scheme based on Smartphone-based body area networks [1].

Traditional offline epidemic control tactics often combine both offline control and model-based measures, such as quarantining or immunizing people to prevent the pandemic from spreading. However, these approaches are ineffective due to either delayed data collection (e.g., utilizing medical surveys or medical records) or unrealistic statistical assumptions about the dynamics of social contact networks. Social contact networks are one sort of social networks [2].These traditional tactics sometimes necessitate social contacts, which individuals must avoid in order to prevent the spread of this pandemic sickness. Instead, use an online social relationship [3].

In this research study, to address the issue of efficacy, we proposed a WBAN-smartphone data collecting system that collects people's health data as well as social contact information at the same time. We combine social and sensor networks, utilizing human body-mounted sensor networks and cell phones. Body sensors can detect influenza from both the body and its environment. Symptoms include fever, high blood pressure, foul-smelling gas, high pressure, rapid heartbeat, chest pain, and so on. The first stage of the process is data collection, which entails collecting influenza's symptoms such as body temperature (BT), oxygen saturation (OS), blood pressure (BP), and respiratory rate (RR) on users' smartphones via body sensors; smartphones can also assist in sensing body gesture information.

Secondly we cluster individuals so that we can determine whether or not to send them to a containment zone based on the value of information obtained from their bodies. The containment zone will be a much larger network that will be difficult to maintain; the people will need to be divided into many clusters based on the severity of their symptoms, and the control approach will be implemented within the clusters. We must first form the cluster and select a cluster head node from among other nodes using this cluster formation technique; this is accomplished using the Artificial Intelligence technique; Ant Colony Optimization (ACO) algorithm, with which we form a cluster based on the severity of vital signs collected.

People with the same range of vital sign severity are grouped in the same cluster, and each cluster is controlled by a cluster head node (a health party chosen to control each cluster and collect information about each patient, which is then transmitted to the cluster head of the next cluster and health authorities). We tested the algorithm's efficacy using both analytical and simulation models in the NS-2 simulator, and the results are based on the random way-point model to demonstrate that the proposed scheme can provide high QoS performance in terms of increased sensing, collecting, and processing health information and transmitting it to the health authority with a high end-to-end delivery ratio, minimal transmission delay, and increased throughput.

The remaining parts of the paper are organized as follows. Section II contains the Related Works. Section III discusses Problem Definition. Section IV contains Implementation of The New Protocol CICSBAN while Section V presents performance evaluations based on simulations. The paper concludes in Section VI.

II. Related Works

Social Sensor Network (WSN) technologies are regarded as one of the key areas for healthcare applications aimed at improving human life quality, and they provide future research directions on wearable and implantable body area network systems for continuous patient monitoring [8].

The authors of [4] proposed a system called Sense Seer which offers configurable analytic services for sensing a human being and understanding the semantics of living activities. This framework exhibits the design concepts and three services.

In paper [5], the author developed a hybrid and distributed environment for gathering data from mobile phones as well as analysing sensory data to provide insights into user behaviour and lifestyles. This solution builds and preserves a cloud-based log file repository for the user.

The authors of [6] review an application called CenceMe which represents the first system that combines interference from individual people in their presence utilizing off-the-shelf, sensor-enabled mobile phones that communicate information via social networks like as Facebook, Twitter, and so on. This app is available for Nokia N95 phones.

In [7], the authors proposed the iCovidCare model for predicting the health status of Covid 19 patients using the ensemble Random Forest (eRF) technique in edge networks. In this study, the scientists used temperature sensor information to construct a rule-based strategy for local edge devices. They were able to identify a patient's risk factor and predict his or her future health state using real-time health monitoring metrics. They employed a data fusion and feature selection method to identify and emphasize the most important features for disease prediction. The suggested iCovidCare model was tested against a covid 19's data set and standard classification models; the former beat traditional models in all study situations, with 95.13% accuracy.

In paper [8], the authors introduced a DP-cluster algorithm based on distance-preserving subgraphs that discovers the appropriate distance-preserving subgraphs and partitions a graph into an arbitrary number of distance-preserving subgraph. Even though these clustering techniques are useful, they have certain downsides because they do not account for both node location and their respective features; as a result, they are frequently not used in the design and execution of epidemic control strategies.

III. Problem Definition

The people with influenza have navigating social interactions and accessing support networks are the main focus of the issue statement for flue in social network environment. These difficulties are frequently made worse by cultural norms and a lack of resources. In the end, this affects social inclusion and well-being and includes challenges with diagnosis, communication, and access to suitable interventions. Recent developments in social networks have made it possible for a large number of people to regularly use a variety of services and connect with various communities of interest through them. A person only uses a portion of these services at any given time, though, either to exchange information with a community of interest (COI) or to consume certain services.

Miniaturizing sensor nodes is necessary to make them wearable or implantable.

In order to increase the lifespan of the sensor nodes and give a longer battery life, energy optimization techniques should be created by combining the link and physical layer functions for wireless devices. When data transmission is not needed, the sleep mode method should be used to ensure that the sensor nodes spend the majority of their time using little electricity. Those devices can sense patient's physiological data which must be divided into essential and non-crucial categories. For instance, vital signs like electrocardiograms may be more significant than temperature for certain individuals, albeit this may vary from patient to patient. As a result, the WBAN system needs to prioritize the crucial information.

Sensor nodes should be equipped with high gain micro antennas to boost transmission reliability and reduce interference which will lower energy usage.

A variable sample rate must be used to optimize each sensor based on its unique properties.

Each sensor node in a WBAN system needs to be optimized in accordance with its sensor's frequency range since, in contrast to other systems, each sensor signal in the sensor network has a different frequency (i.e., not uniform). Furthermore, since some physiological signals that are not critical, like temperature data can only be measured over extended periods of time, WBANs will perform better if the "adaptive" communication protocol is used to account for these variations in the system, which will undoubtedly increase the system's power efficiency. Several gateway devices must be created to interact with the current wireless systems in the healthcare sector in order to guarantee ongoing remote monitoring of WBANs. The primary function of these gateways will be to facilitate communication between the CCUs and distant PCs or mobile devices.

In order to allow patients to move freely in major medical applications, WBANs need incorporate a transmission mechanism. It can be used to follow a patient about a hospital or to monitor the areas where the patient is going about their everyday business outside. If a patient leaves the room or moves out of a CCU's range, an alarm feature can be activated. Security is another crucial element of WBANs. Finding and creating the fundamental software components is necessary to support a safe and effective wireless network. Only authorized individuals should be able to access data at faraway locations. Coordination between software applications and hardware elements is necessary to enable dependable and secure connections.

The sole purpose of personal health monitoring systems was to gather data. Such sensors are impracticable for continuous monitoring and early diagnosis of health issues because data processing and analysis are done offline. Unmanageable wires connecting the sensors to the monitoring system are a common feature of physical rehabilitation systems with several sensors. These cables may restrict the patient's range of motion and comfort, which would impair the measurement's accuracy.

In WBANs, individual sensors frequently function as stand-alone systems and typically lack the flexibility and integration with external devices. In order to resolve coexistence concerns, WBAN systems should eventually have their own standards for wireless communication and data collection,so, the need for online effective measures to contain and stop the spread of such pandemic using effective epidemic control strategies which effectively capture, gather health and social contact information simultaneously, take quarantine measures and finally have report-capability often arises.

IV. Implementation of The New Protocol CICSBAN: Analytical Modeling

In this paper, we propose a new robust scheme, the Influenza Prediction model which has two data sources: the wireless body sensor network (WBSN) and a set of body vital signs, namely Body Temperature (BT), Oxygen Saturation (BT), Blood Pressure (BP), Respiration Rate (RR), and Heart Rate (HR), of both infected and healthy individuals. These vital signs are utilized to collect internal and external physiological data for daily health monitoring and predicting the spread of Influenza infection throughout society. These vital indicators are then sent to processing devices (one for immediate decision making and the other for future disease prediction operations) via gateway devices via WIFI (Wireless Fidelity).

This monitoring program helps to reduce the spread of Influenza among people. In this proposed approach, we use several robust strategies for network management and data packet distribution, including clustering and routing; each strategy is implemented and completed independently.

The proposed model contains three phases.

Phase I: Human Body Sensing

Body sensing is the first stage of implementing the proposed strategy. We use virtual vital sign sensors/detectors that are intimately attached to the skin in sites other than the patient's wrist and finger. This provides significant advantages for examining Influenza’s symptoms. Because this virus is primarily a respiratory disease, measurements of respiratory indicators such as body temperature (BT), oxygen saturation (BT), and respiration rate (RR) taken directly from the thorax are expected to offer a lot of information.

We simulate the real sensor, developed by Sibel Health for wireLow ICU-grade monitoring of complete vital signs, including pulse oximetry, which has an excellent interface to the intrathoracic cavity for high-fidelity recordings of respiratory activity coming from various sources such as intensity, cough frequency, respiration rate, duration, sneezing, and wheezing. It can also monitor the heart and get data on cardiac amplitude, heart sounds, and heart rate [https://www.sibelhealth.com].

We have added additional features to the aforementioned device because it has been discovered that continuous monitoring using these technologies presents both opportunities and challenges in data analytics and data management, given the exceptionally high volumes and diversity of health information. Additional aspects of our simulated device include scalable data back ends that securely transport, store, process, and make patient information available in accordance with HIPAA regulations.

Interoperability can be achieved by linking this information to other disparate sources, such as electronic health records, to enhance the information content, as digital health data involves proprietary formats and incompatible systems, resulting in a fragmented silo.

The structure and functionality of the proposed model

This model is made up of Edge devices that make fast judgments based on collected vital indicators such as body temperature (BT), oxygen saturation (BT), blood pressure (BP), respiration rate (RR), and heart rate (HR) in both sick and healthy individuals. Edge devices are set locally as

$E=\{E1,E2,\ldots,En\}$ and centrally as $S=\{S1,S2,\ldots,Sm\}$.

The local edge devices quickly transfer the collected vital signs to the phones of health officials. We developed another model, the prediction model, which predicts the likelihood of infection with coronavirus illness. The model includes the following phases:

1) Data fusion;

2) Data reprocessing with feature selection;

3) Disease prediction classifier.

1) Data Fusion

We present a fusion technique that extracts features and analyses real-time data from prior body sensing activities. The data presented is raw data and might come from a variety of sources; it contains both helpful and useless information; we must first produce a more accurate and useful dataset. Data fusion techniques have two levels. In the first level, unuseful data is filtered. We extract Body Temperature (BT), Oxygen Saturation (OS), Blood Pressure (BP), Respiratory Rate (RR), and other chronic disease parameters to assess the severity of INFLUENZAon the patient. Medical records without a history of chronic diseases are removed.

We then merge and save it as comma-separated values in.SVC format. We employed data processing approaches before applying data prediction operations. We must first preprocess real-word data utilizing missing-data techniques by adopting a simple Kalman filter method for reducing noise, inconsistencies, and duplicate records.

We reprocess the fused data to reduce noise and filter out missing data. We thus use various data mining techniques, and finally, we pass them through the RF classifier [12]. At this stage, we can predict influenza of the patient, we then store the analyzed data in the computer for analysis and prediction of Corona-virus.

2) Data Reprocessing through Feature Selection Techniques

Before performing data prediction operations, we must first pre-process real-world data using missing-data techniques such as a simple Kalman filter method to remove noise, inconsistencies, and duplicate records, as well as feature selection, normalization, and so on. [13]

3) Classification model for disease prediction

Validation results of instant decision making

The proposed scheme aims to validate an instant decision-making model for Influenza disease by varying patient body temperature, oxygen saturation, blood pressure, and respiratory rate. The model will make instant decisions at the local edge device with minimal delay.

Influenza Classification Rules

i. Body temperature: The patient's body temperature was measured in Celsius (36.4 for normal, 36.6-37.5 for moderate, and ≥38 for severe).

ii. Oxygen Saturation: Blood oxygen saturation in mm Hg (95-100: Normal; 80-95: Moderate; 65-80: Severe).

iii. Blood pressure: The systolic pressure of circulating blood is measured in mmHg (less than 120: Normal); 120-130: Moderate; and 130-180: Severe).

iv. Respirator Rate: The patient's respiratory rate in bpm (8-25: Normal); (26-35: Moderate); (> 35: Severe)

Table 1: Influenza's Patient Classification Rules

Body Temperature (BT)	Oxygen Saturation (OS)	Blood Pressure (BP)	Respiratory Rate (RR)	Condition
Normal	Severe	Severe	Normal	Mild
Normal	Severe	Moderate	Normal	Mild
Normal	Severe	Normal	Normal	Mild
Normal	Moderate	Severe	Normal	Mild
Normal	Moderate	Moderate	Normal	Mild
Normal	Moderate	Normal	Normal	Mild
Normal	Normal	Severe	Normal	Mild
Normal	Normal	Moderate	Normal	Mild
Normal	Normal	Normal	Normal	Mild
Moderate	Severe	Severe	Normal	Moderate
Moderate	Severe	Moderate	Moderate	Moderate

Moderate	Severe	Normal	Moderate	Moderate
Moderate	Moderate	Severe	Severe	Moderate
Moderate	Moderate	Moderate	Moderate	Moderate
Moderate	Moderate	Normal	Normal	Moderate
Moderate	Normal	Severe	Severe	Moderate
Moderate	Normal	Moderate	Moderate	Moderate
Moderate	Normal	Normal	Moderate	Moderate
Severe	Severe	Severe	Moderate	Severe
Severe	Severe	Moderate	Normal	Severe
Severe	Severe	Normal	Normal	Severe
Severe	Moderate	Severe	Severe	Severe
Severe	Moderate	Moderate	Severe	Severe
Severe	Moderate	Normal	Moderate	Severe
Severe	Normal	Severe	Severe	Severe
Severe	Normal	Moderate	Severe	Severe
Severe	Normal	Low	Severe	Severe

According to table 1, with the proposed rule-based classification strategy, the hospital authority may easily take required action on Influenza patients and request that they isolate themselves or stay at home/hospital based on the aforementioned severity criteria. The Fuzzy Inference Engine generates a total of 27 rules for disease severity based on linguistic values (p). For example, an adult patient with normal body temperature, moderate oxygen saturation, severe blood pressure, and normal respiratory rate.This patient has a low risk of being picked for isolation because his or her influenza condition is mild, but the patient with all vital signs being severe may be selected for isolation because the Influenza condition is severe. The same technique is taken to generate all 27 rules.

Phase II: Cluster Formation

The cluster creation process divides the network into separate groups of nodes, each of which constitute a cluster. The major goal of this strategy is to lower transfer rates and assign each node to a cluster, making transmission between them easier.

We have three clusters, each representing a group of people in the same condition based on the severity of Influenza in each patient. The first cluster contains patients with the Normal Influenza condition, the second cluster contains patients with the Moderate Condition, and the third cluster contains patients with the Severe Condition. Grouping patients into clusters allows health officials to manage patients more effectively and take fast action when necessary.

Cluster formation algorithms are provided in the next section:

Algorithm: Cluster Formation Algorithm

BEGIN

N: Number of all network nodes

C: Condition of the Patient

P: Patient

i=1

While (i<=N) {

Collect Body Temperature (BT) of P_i

Collect Oxygen Saturation (OS) of P_i

Collect Blood Pressure (BP) of P_i

Collect Respiratory Rate (RR) of P_i

Set C according to BT, OS, BP, and RR of P_i

If C=’Mild’, **Then**

P_i is sent to ‘Mild’ Cluster

Else If C=’Moderate’, **Then**

P_i is sent to ‘Moderate’ Cluster

Else Then

P_i is sent to ‘Severe’ Cluster

End If

i=i+1

End While

END

Overall the proposed scheme is summarized in the following figures.

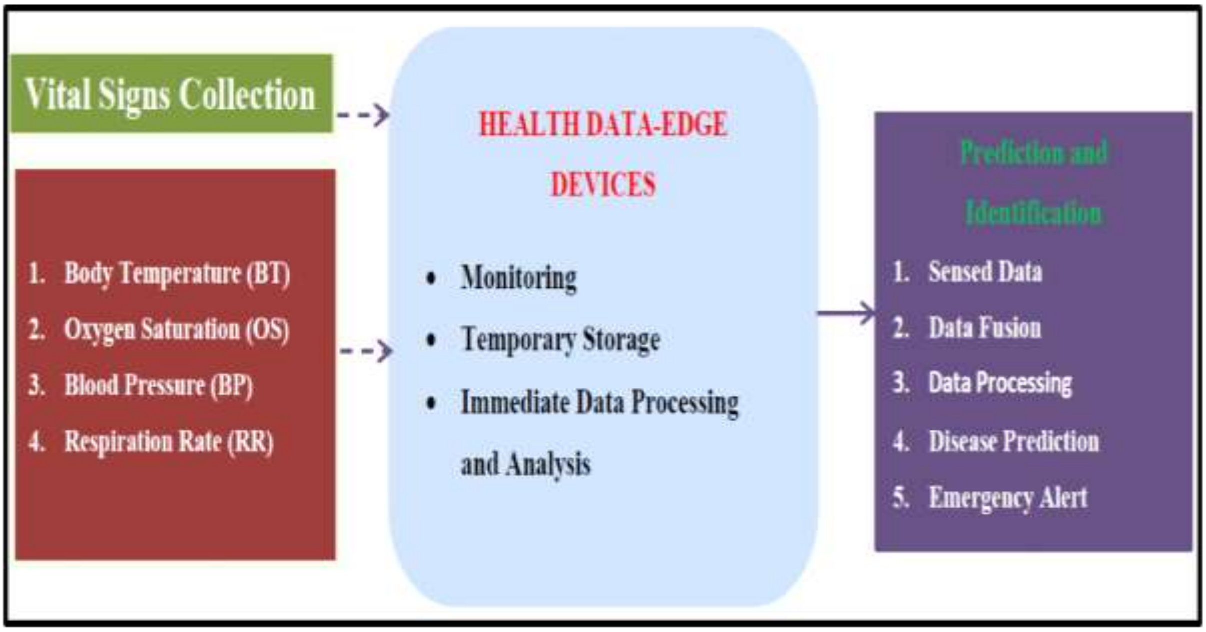

Figure 1: Vital Signs Collection

This proposed Protocol can help various organizations, whether public or private, or in any public place where a large number of people meet, to test for visitors for influenza using smartphones. Once a visitor is found with the pandemic with the moderate and high Influenza conditions, they are immediately isolated and put into the cluster (a cluster will be a place where people with the same severity of influenza), their identities (personal identities and the cluster they belong to), They are subsequently isolated in the Cluster for further treatment and to suppress the societal spread of these pandemic diseases.

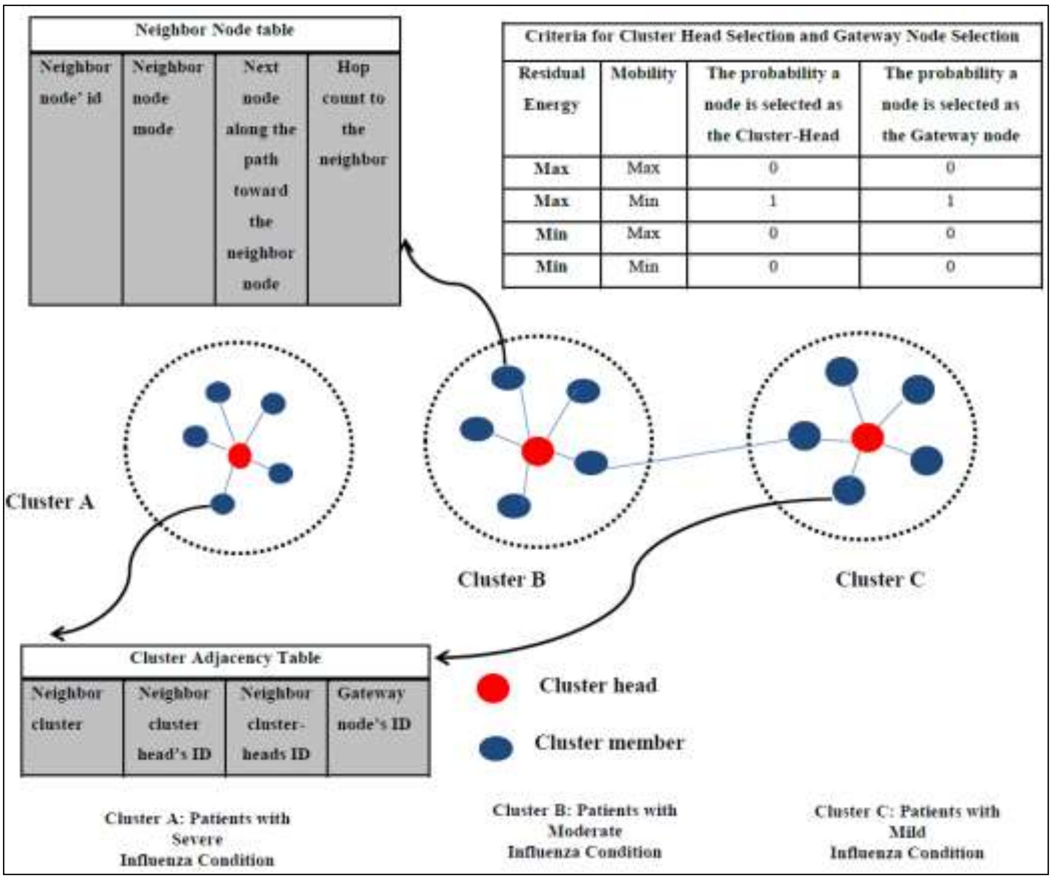

Figure 2: Structure of the Proposed Influenza Prediction Model.

V. Performance Evaluations

5.1 Introduction

In this section, we compare our proposed mechanism CISCBAN (Cluster-Based Influenza Control Mechanism via Smartphone-Based Body Area Networks) to existing QoS protocols such as Destination-Sequenced Distance-Vector routing (DSDV), Ad Hoc on Demand Vector Routing Protocol (AODV), and Temporally ordered routing algorithm (TORA). Through simulation research, we show that the out proposed scheme outperforms the old ones. The performance evaluation tries to discover the best channels for routing data packets in Wireless Body Sensor Networks in order to achieve good QoS. The algorithms are briefly outlined below: .

5.2 Destination-Sequenced Distance-Vector routing (DSDV)

DSDV is a proactive routing protocol for mobile ad hoc networks (MANETs). It solves the "count-to-infinity" problem found in distance-vector protocols by employing sequence numbers to assure loop-free routing. Each node keeps a routing database containing the destination, next hop, metric (hop count), and sequence number. DSDV is a powerful routing technique for MANETs that uses sequence numbers to overcome the limits of classical distance-vector routing. However, its proactive approach and reliance on periodic updates might result in considerable overhead, making it less suitable for very large or particularly dynamic networks [16].

5.3 Ad Hoc on Demand Vector Routing Protocol (AODV)

It's a reactive/on-demand routing protocol. It is an extension of the dynamic source routing protocol (DSDV) that helps to overcome the limitations of the dynamic source routing protocol. In DSDV, when the source mobile node delivers a data packet to the destination mobile node after route discovery, the header includes the entire path. As a result, as the network size increases, so does the length of the whole path and the size of the data packet header, causing the entire network to slow down. As a result, the Ad-Hoc On Demand Vector Routing protocol was developed to address this issue. The key difference is in how the path is stored; in TORA, source nodes do not keep complete path information, and each node does not store information about its previous and next node. It also has two phases: route discovery and maintenance [16].

5.4. Temporally ordered routing algorithm (TORA)

Information can go from nodes with greater heights to nodes with lower heights. Information can thus be viewed as a fluid that only flows downward. TORA enables loop-free multipath routing by always maintaining a collection of totally ordered heights, as information cannot 'flow uphill' and hence cross back on itself. TORA 's core design concept is the localization of control messages to a restricted number of nodes around the point of a topological change. To accomplish this, nodes must keep routing information about adjacent (one hop) nodes. The protocol has three basic functions:

Route creation and maintenance and Route erasure [17].

5.5 Simulation Environment

NS2, or Network Simulator 2, is a popular open-source, discrete-event network simulator that is primarily used for research and instruction in computer networking. It enables users to simulate numerous network protocols and behaviors, both wired and wireless, by combining C++ and OTcl/Tcl scripting. NS2 has become a popular choice for network simulation due to its versatility and ability to mimic a wide range of network settings. [11].

Table 2: Parameter values for simulation

Parameter	**Values**
Number of nodes	60
Interface type	Phy/WireLowPhy
Channel	WireLow Channel
Mac type	Mac/802_11
Queue type	Queue/DropTail/PriQueue
Queue length	200 Packets
Antenna type	Omni Antenna
Propagation type	TwoWayGround
Size of packet	512-1024
Protocol	CICSBAN
Traffic	CBR
Simulation area	1500M*1500M
Node mobility speed	1…20 m/s

4.3 Simulation Parameters

Simulation parameters describe a network's performance. We utilize the following three simulation parameters to compare the performance of our work to the current ones:

The Packet Delivery Ratio is a fraction of the total amount of data packets sent to the destination. This fraction represents the level of packet delivery. A higher packet delivery ratio indicates better protocol performance. ones:

Packet Delivery Fraction=∑ Number of received

packets / ∑ Number of sent packets (3)

Throughput is the total number of packets sent for the entire simulation time. It is expressed in bits per second (bps).

Throughput = Received data / Data Transmission Period (4)

The end-to-end delay fraction is the average time required for a packet to reach its destination. Many factors, including the route discovery cycle and the queuing procedure employed during data packet transmission, can contribute to this phenomenon. Only data packets that were successfully delivered to their destination are counted. The value of end-to-end delay determines the protocol's performance; a smaller ratio indicates that the protocol performs better.

End-to-end delay ratio=∑ (Packet-arrive time – Packet-send time) / ∑ Number of connections (5)

5.4 Comparative Analysis

We compare the performance of our new mechanism CICSBAN to those in the literature using different routing metrics (protocols).

A. Performance Evaluation with PDR

CICSBAN's performance is compared to existing QoS algorithms such as AODV, TORA, and DSDV utilizing the Packet Delivery Ratio parameter metric in OPNET Simulator.

Table 3: PDR of CICSBAN and AODV varying number of receivers

Number of Receivers (Nodes)	**Packet Delivery Ratio**		
	CICSBAN	**DSDV**	
10	0.95	0.935	
15	0.953	0.938	
20	0.953		0.94
25	0.953	0.945	
30	0.953	0.948	

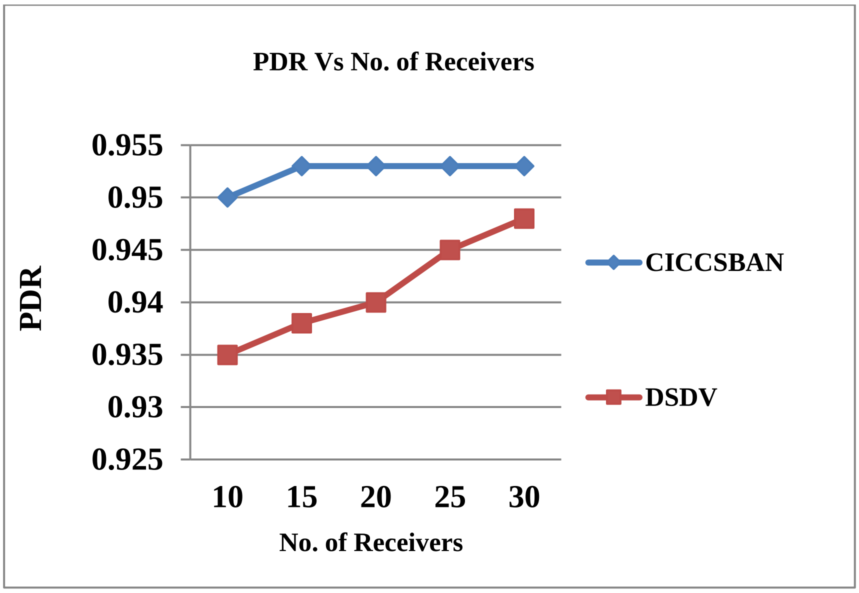

Figure 3: PDR vs. No. of Receiver Nodes

As shown in Table 3 and Figure 3, the PDR of the new algorithm is compared to DSDVs. The performance evaluation takes into account the number of receivers. During the simulation, the number of receivers varies between 10 and 30 nodes. CICSBAN achieves the greatest performance due to two key features: good connection quality and the ability to select a stable routing. One notable discovery is that the PDR of both methods steadily grows in proportion to the number of receivers. However, the new algorithm, CICSBAN keeps a high PDR which DSDV never attains, the outperformance of CICSBAN is hence proved.

B. Performance Evaluation with Delay

As shown in Table 4 and Figure 4, when considering end-to-end delay and varying the number of nodes, CICSBAN's delay remains lower than that of existing protocols during the overall simulation time, even as the number of nodes increases, making the CICSBAN protocol superior. The CICSBAN method achieves the optimum performance behavior by selecting paths with reduced distance and reachability values as optimal paths.

Table 4: End-to-End Delay of CICSBAN and existing approaches

Number of Nodes	End to end delay [(secs)]			
	CICSBAN	DSDV	AODV	TORA
10	0.5	1.2	1.5	1.8
15	3	2.5	4.3	3
20	7	8.8	8.8	9.5
25	9	12	12	13
30	12	15	16	16

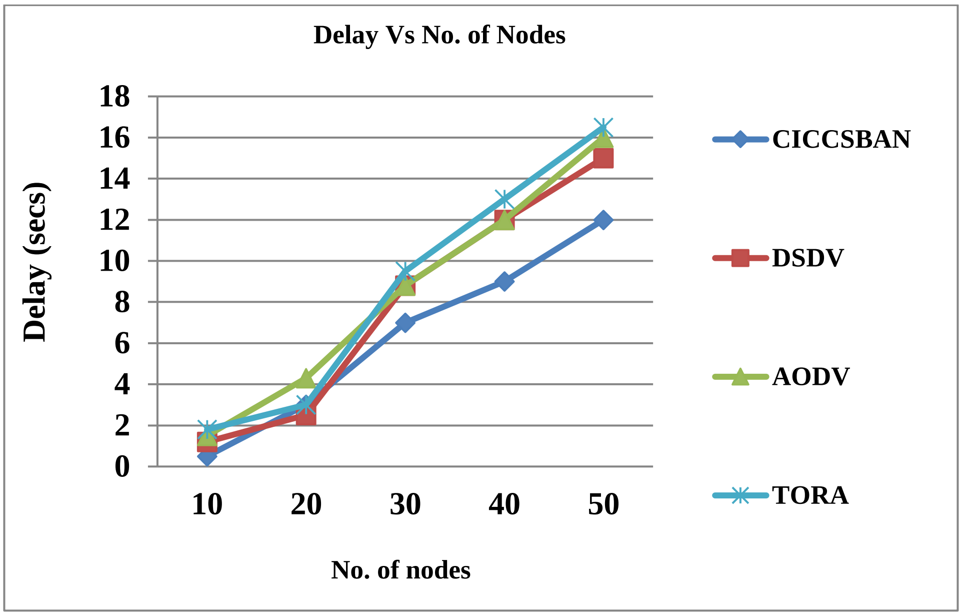

Figure 4: End-to-End Delay vs. No. of Nodes

In Table 5 and Figure 5, the new protocol CICSBAN is compared against DSDV. CICSBAN once again beats the DSDV protocol by maintaining a lower end-to-end delay ratio for both small and large numbers of receivers.

Table 5: Delays for CICSBAN and DSDV with the varying number of receivers

Number of Receivers (Nodes)	End-to-End Delay [(secs)]	
	CICSBAN	DSDV
10	11	12
15	11.5	12.6
20	11.8	12.9
25	12.2	13.5
30	12.5	14

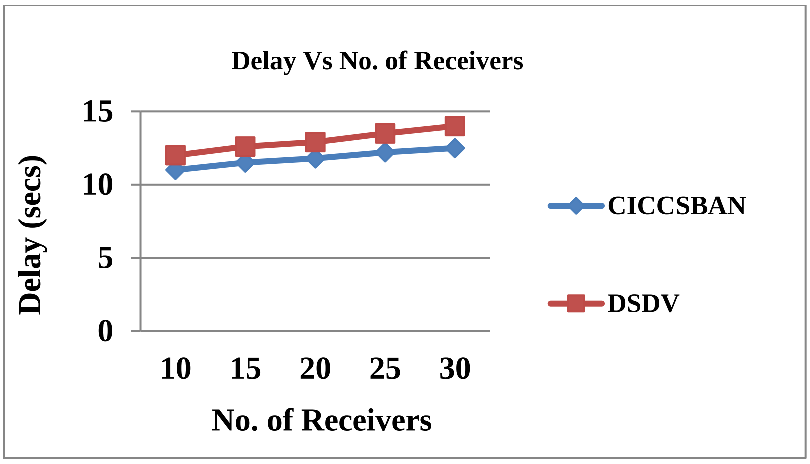

Figure 5: End-to-End Delay vs. No. of Receiver Nodes

C. Performance Evaluation with Throughput

Table 7 and Figure 7 show the performance of the novel algorithm CICSBAN versus TORA. The findings obtained by adjusting the network size, i.e. the number of nodes, while using throughput as an evaluation parameter metric show that CICSBAN has the highest throughput ratio when compared to the current ones. alues are first chosen as optimal pathways.

Table 6: Throughputs of CICSBAN and TORA varying number of receivers

Number of Receivers (Nodes)	Throughput [kb/s]	
	CICSBAN	TORA
10	0.97	0.93
15	0.968	0.927
20	0.965	0.925
25	0.963	0.923
30	0.96	0.921

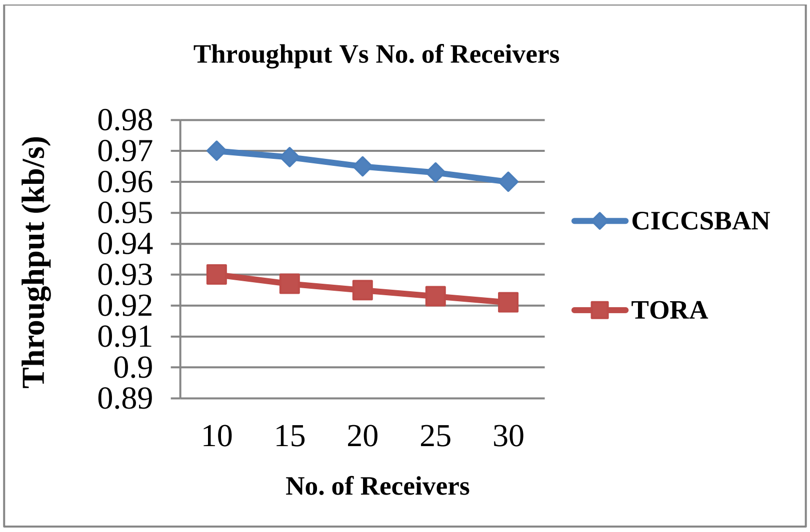

Figure 8: Throughput vs. No. of Receiver Nodes

VI.CONCLUSION

In this study, we proposed an efficient cluster-based INFLUENZAControl-Prediction mechanism using Smartphone-Based Body Area Networks to collect vital signs, group individuals into clusters based on the severity of their symptoms, and finally transmit both patient and cluster information to health authorities for immediate decision-making.

Unlike typical offline control or traditional model-based approaches, our mechanism is created based on real-time social contact and health information, allowing us to decide the ideal number/set of nodes to remove in order to effectively contain the epidemic spread. The suggested cluster-based control technique consists of three parts. In the first step, we collected various vital indicators from the human body; in the second phase, we divided the population into several clusters based on the severity of the symptoms. rities for instant decision-taking. In the third step, critical node/set identification methods are used inside or between clusters, and the collected data is sent to the health authorities' devices for immediate decision-making. ms. rities for quick decision-making.

As previously discussed, some information about social contact or vital indications may not be collectible. Another weakness of this study is the use of simulations. In this investigation, we only examined the suggested protocol in terms of routing; however, future studies will include important assessments of this mechanism in terms of clustering and vital sign detection. Our key contributions include the development of inter- and intra-cluster epidemic control approaches, as well as the transmission of collected data to health authorities. In all study instances, CICSBAN exceeds existing protocols in terms of rapid and effective information dissemination since it can raise end-to-end packet delivery ratio, reduce end-to-end delay, and increase throughput.

References

[1] Padron R. (2020). E. Vaccines for SARS-CoV-2: lessons from other coronavirus strains. *Infect. Dis. Ther*. 9, 255–274.

[2] Ortiz-Prado, E. et al. (2020). Clinical, molecular and epidemiological characterization of the SARS-CoV2 virus and the coronavirus disease 2019 (COVID-19), a comprehensive literature review. *Diagn. Microbiol. Infect. Dis*. 98, 115094.

[3] R. Nussbaum, A. Esfahanian and P. Tan (2010), Clustering Social Networks Using Distance-Preserving Subgraphs, *International Conference on Advances in Social Networks Analysis and Mining*, pp. 380-385.

[4] Mathematical Modelings to characherize early Epidemic Growth: A Review.

[5] M.Z. Alam , M.S. Rahman , M.S. Rahman (2019) , A random forest based predictor for medical data classification using feature ranking, *Inform. Med. Unlocked 15*, 1–12.

[6] Mainak A.(2021). Ambigavathi Munusamy, iCovidCare: Intelligent health monitoring framework for INFLUENZAusing ensemble random forest in edge networks, *Internet of Things.*

[7] Shabbir N, Nawaz R, Iqbal MN, Zafar J. (2015). Routing protocols for a small scale WLAN based wireless sensor networks. *In: 9th International Conference on Sensing Technologies. New Zealand: I*EEE.

[8] Bakr BA, Lilien L. LEACH-SM (2011). A protocol for extending wireless sensor network lifetime by management of spare nodes. In: International Symposium on Modelling and Optimization in Mobile, Ad Hoc and Wireless Networks (WiOpt); *IEEE; New Jersey, Princeton*.

[9] Ehsan S, Hamdaoui B. (2012). A survey on energy-efficient routing techniques with QoS assurances for wireless multimedia sensor networks. *IEEE Communications Surveys & Tutorials*, 265-278.

[10] Opnet Technologies, www.opnet.com.

[11] S. Din , A. Paul (2019). Smart health monitoring and management system: toward autonomous wearable sensing for internet of things using big data analytics,Future Gener. Comput. Syst., 611–619.

[12] S. Narayan , E. Sathiyamoorthy (2019). A novel recommender system based on FFT with machine learning for predicting and identifying heart diseases, *Neural Comput.*, 93–102.

[13] S. Virgeniya , E. Ramaraj (2019). Predictive analytics using rule based classification and hybrid logistic regression(hlr) algorithm for decision making, *Int. J. Sci. Technol. Res. 8*, 1509–1513.

[14] Y. Kumar , G. Sahoo (2013) , Prediction of different types of liver diseases using rule based classification model, *Technol. Health Care*, 417–432.

[15] J. Christopher (2019). The science of rule-based classifiers, in: Proceedings of the 9th International Conference on Cloud Computing, *Data Science Engineering (Confluence)*, 299–303.

[16] Perkins Charles E., Bhagwat Pravin: Highly Dynamic Destination-Sequenced Distance-Vector Routing (DSDV) for Mobile Computers, London England UK, SIGCOMM 94-8/94.[17] Singh, U., Samvatsar,M., Sharma, A., Jain, A.K.(2016). Detection and avoidance of unified attacks on MANET using trusted secure AODV routing protocol. 2016 Symposium on Colossal Data Analysis and Networking (CDAN), 1-6.

[18] Gatete M. & Vetrivelan, N. (2015). Performance evaluation of four hybrid routing protocols for low- and high-density MANETs, International Journal of Computer Science & Engineering Technology (IJCSET)