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RESEARCH ARTICLE

The Key Criteria for Predicting Unusual Behavior in the Elderly With Deep Learning Models Under 5G Technology

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ABSTRACT Deep learning algorithms and technology based on 5G networks may be able to help identify unusual behavior in elderly people. Because 5G networks have a lower latency and a greater bandwidth, it is possible to use more complex algorithms and larger data sets for training and detection in a real-time. On top of that, real-time analysis of the data gathered through in-home monitoring of the elderly can become much simpler to carry out with the help of 5G's potential to simplify the process. However, the system needs to be developed in a way that it considers the preferences of the most important criteria of elderly people, who have more requirements in terms of their living situation and the environment in which they live. Therefore, this study advocated using "Decision Making Trial and Evaluation Laboratory" (DEMATEL) to analyze the most crucial criteria (feature) required for creating a model for identifying odd behavior in elderly persons. Convolutional Neural Networks (CNNs) and Long Short-Term Memories (LSTMs) are adopted in detecting unusual behavior in the elderly after the analysis key criteria for predicting unusual behavior in the elderly by DEMATEL. The research established a concept by linking the SIMADL dataset with the dimension of elderly people's behavior and performed an experimental analysis using both CNN and LSTM. Performance evaluations show that the LSTM performs better in detecting unusual behavior in elderly persons with 96% accuracy. Depressive disorder is the most significant aspect of ageing that might lead to a typical unusual behavior in elderly persons, according to DEMATEL analysis.

INDEX TERMS 5G adoption, elderly behaviors, falls detection, gesture interpretation, facial recognition, depressed disorder detection.

I. INTRODUCTION

5G adoption has skyrocketed in recent years and Governments and telecoms companies have invested heavily in 5G network research, development, and deployment [1]. As of 2021, about 100 countries have commercially installed 5G networks, and the GSM Association expects that many more will soon [2]. Some eldercare systems incorporate many healthcare issues that 5G technology could be seen to transform healthcare in many ways. It is expected that 5G networks would enable medical professionals to remotely monitor patients and provide treatment to them, this will be especially helpful for patients who are elderly or who suffer from chronic illnesses. [3]. 5G networks will allow remote monitoring of elderly patients at home, In addition, high-definition video conferencing carried via 5G networks will make it possible to conduct virtual visits to the physician, that is, 5G networks can transmit CT and MRI scans that could enable remote clinicians to analyses and diagnose medical images in real time This expands medical alternatives for rural and underserved patients [4].

It is possible that the technology of 5G, in conjunction with the algorithms of deep learning, might be utilised to improve real-time detection of phenomena [5]. In a similar vein, the technology of 5G, in conjunction with the algorithms of deep learning, may be used to improve the detection of

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elderly people engaging in unusual behavior when they are at home [6]. Due to 5G networks' higher data transfer rates and reduced latency, more complex algorithms and data sets can be used for training and detection [1]. 5G also makes it feasible to employ more connected devices to collect more data and execute real-time analysis in order to have a timely judgement for any situation. This can be accomplished by performing real-time analysis. However, the implementation of such a system must take into account the well-being of the elderly people and the unusual behavior that might arise. For this reason, the current study draws on the features of the elderly people gathered from Almutari et al. [7] from the perspective of designing a system for detecting elderly people behavior, such as "Abnormal Behavior Detection (AB)", "Falls Detection (FD)", "Hand Gesture Detection (HG)", "Facial Recognition Detection (FR)", "Depressed Disorder Detection (DD)", and "Body Gesture". On the negative side, there are numerous causes of unusual behavior that are related with medical and psychiatric diseases. On the positive side, there are additional causes of unusual conduct that entail a change in a person's recognised negative attitude to a good attitude [8].

The operational definition of elderly people "Unusual behavior" for this current research involves performing actions that are not normal for the person, which are the behavior that does not happen very often and does not appear very often. This definition emphasizes the fact that "unusual behavior" involves performing actions that are not normal for the elderly people. For instance, elderly at home unusual behavior include "leaving fridge door open", "leaving oven on for a long time", "leaving main door open", "leaving bathroom light on", "leaving TV on", and "leaving bedroom light on" and "wardrope open" [8]. Therefore, in order to detect such features in real time, a high-speed network technology such as 5G and a power detection technique such as deep learning was necessary.

This research was conducted with the goal of determining which component or factors are most important in recognizing the behavior of elderly people when they are at home and managing their lives for day-to-day activities. A focus is placed on the social elements of adopting 5G technology for the purpose of observing the behavior of elderly persons while they are at home and managing their lives for day-to-day activities. This is done with the intention of improving the quality of life for these individuals. The study also identifies the most significant component or variables that can be used to construct a model that is most adaptable to detect factors of the behavior of elderly people while they are managing their lives for day-to-day activities while they are at home.

The paper's key contribution is as follows:

- The research demonstrates that 5G network technology is amenable to the creation of a system that can keep tabs on the social lives of the elderly in their homes, assist them with everyday activities, and report any unusual behavior they may be engaging in. The research also confirmed its importance for keeping tabs on the elderly and being prepared for any eventuality.
- The study identifies important parameters that can be used to track the well-being and actions of the elderly in their own homes. These features are gleaned via an examination of expert-judged criteria for making decisions. In the study, the research was able to isolate characteristics of the elderly that are indicative of the beginnings of aberrant behavior and helpful for independent living.
- The study, was able to mapped activities from Alshammari et al. [8] dataset with Abnormal behavior" dimension from Almutari et al. [7] in order to conceptualized and examine the key criteria that influence an unusual behavior to further use deep learning for detecting these attributes.
- The study examines the social implications of using 5G technology to keep checks on the elderly at home and manage their day-to-day activities, highlighting the most important component or characteristics that can be used to construct a model best suited to detect unusual behaviors. The research also highlighted the importance of deploying 5G and deep learning together, as they are the most effective solutions for real-time operations. A system that aids the elderly in managing their affairs at home can be developed through the sequential integration of subjective and experimental evaluations. The results indicate that 5G network technology should be used to track the social activities of the elderly at home and provide support for them as they deal with the challenges of daily life. which validated its usefulness for keeping a close eye on the wellbeing of the elderly and acting swiftly in case of an emergency.

The following is the structure that the content of this paper follows: In addition to this section, which provides an overview of the research, section II focus on the previous research studies that is relevant to the research. In Section III, the paper gives an explanation on the research methodology, as well as the models; in Section IV, the paper gives the evaluation of the models; in Section V, the paper discusses the findings of the study; and in Section VI, the paper provides an overview of the conclusions of the paper.

II. RELATED WORK

It's important to note that 5G networks are still in the early stages of deployment and adoption, and more research and development is needed to fully realize the potential of 5G in monitoring systems for the elderly [10]. Some studies have focused on the potential benefits of 5G networks for remote monitoring and telemedicine, while others have looked at the use of IoT devices and sensors in combination with 5G networks to track vital signs and monitor the health status of elderly individuals.

Berlet et al. [11] show that digitalization influences modern living in various ways, including the expanding number of medical care options and telemedicine apps. 5G mobile communication technology can meet the needs of this digitalized future with large bandwidths, low latency, and excellent quality of service, enabling wireless real-time data transmission in telemedical emergency health care applications. The research develops and evaluates a clinically appropriate framework for 5G usability tests to enable mobile ultrasonography in preclinical diagnostics over 5G networks. The research found that the 5G network permitted bidirectional data communication between the ambulance and the remote hospital, allowing ultrasound and video camera data to be transmitted and received. This is one of the famous success story on the adoption of 5G in medical field. There are many other studies which deals with the use of 5G networks for remote health care service.

The accuracy of transmitting perinatal information such as a cardiotocogram is tested by Naruse et al. [12] utilising an experimental station equipped with a 5G transmission technology. All data were shown to have been transferred with a delay of less than 1 second, according to the results. There was no degradation in the quality of the cardiotocogram waveform images, and the transmission did not break up at any point. The ultrasound examination and video movie transmissions looked great. Li et al. [13] established that there is a growing demand for the implementation of 5G-enabled robot-assisted laparoscopic telesurgery in the field of urology; however, substantial evidence regarding the feasibility of its application is still scarce, necessitating an investigation into the aforementioned topic. The study's findings suggest that using 5G technology in tandem with surgical robots could offer a promising new option for the treatment of kidney malignancies via telemedicine. Other studies associated to the implementation of 5G technology include the work that determined that remote gastrointestinal examinations using a 5G network in real time are a practical and secure way for observing stomach and small bowel [14]. Using a 5G network a teleoperated surgery demonstrated a seamless flow of tasks under the guidance of an expert surgeon [15]. Finally, vide an in-depth analysis of the current state of 5G-enabled smart healthcare IoT technologies and the critical factors influencing its deployment has been presented in Ahad et al. [16].

In terms of the research on monitoring of elderly, Dzogovic et al. [17] conducted one of the most significant studies on the impact of 5G on the monitoring of the elderly, finding that a dedicated "network slice" for the aged care market was essential. The radio frontend will be divided into a separate User plane and a separate Control plane. Therefore, the network slice needs to be adaptable and adjustable to accommodate various surfacing needs. The study also shows that further privacy protection procedures and assets should be added to this type of architecture. Thuemmler et al. [18] look into the 5G needs for telemetric cardiac monitoring by analysing data from a joint project on early geriatric rehabilitation of elderly patients in a care of the elderly department following minimal invasive and conservative treatment at a specialised cardiology unit in Leipzig, Germany. Individualized medicine, also known as Precision Medicine, is one of the fastest-growing industries, and the research shows that 5G will be able to fully support this trend. Ultimately, 5G technology has the potential to improve the efficacy and efficiency of healthcare in hospitals, as it is well suited for a wide range of real-time monitoring options. Hossain and Muhammad [19] developed a framework that will significantly advance 5G by facilitating the delivery of compassionate, individual healthcare that takes emotional context into account. A networked healthcare system that can recognise and respond to patients' emotions served as the foundation for this system's design. The presence of a carer is warranted if the feeling is identified as pain. The proposed system was put through its paces in a series of studies designed to prove its worth, and it came out on top with an impressive 99.87% accuracy rate for emotion recognition. According to the findings of Hamm et al. [20], the provision of healthcare in rural areas is met with a unique set of obstacles, the likes of which make the provision of homecare for elderly people as well as cross-sectoral integrated care for chronically ill and multimorbid patients extremely difficult and expensive. Because of this, the research established a platform based on 5G technology, which makes it possible to test and evaluate digital applications within the context of rural healthcare.

There are many other previous research studies that uses machine learning and deep learning for the deployment of a system for monitoring elderly people. Crucial to this is the work of Xu et al. [21] which reveals the success of system for older people's susceptibility to depression was predicted using a multi-task learning for deep LSTM approach. Furthermore, a bio-inspired neural network was utilized for development of a "smart home" that has been found to be a perfect area for service devices, allowing for constant, remote monitoring and control of all activities within [22]. In order to improve the precision with which elderly people activities may be identified, Mishkhal et al. [23] created a CNN-based activity recognition system. This is just one application of the CNN being utilised by many initiatives to advance the state of the art in intelligent devices for assisting with the healthcare needs of the elderly in a technologically advanced setting. CNN were proposed in Noreen and Siddiqui [24] for AI-enabled robots to aid the elderly. The robot's CNN-based object recognition technology helps the elderly individual. The elderly person can just speak into it to activate it and learn more about the alert. The CNN model attained a performance accuracy of around 95%. Finally, another study that utilized CNN was proposed for multi-domain activity classification in geriatric healthcare [25]. The retrieved pattern characteristics allow the CNN to recognise and categorise six separate activities. According to the findings, the CNN was successful in achieving an accuracy rate of 91%.

It is crucial to note that the aforementioned works [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20] are still focusing on the implementation aspects of 5G in connection to its usage in the medical field. This is something that has to be brought to having a good attention. However, there has not been a lot of discussion on how to leverage the introduction of 5G technology to the monitoring of elderly people for unusual behavior in the context of practical applications. This is a problem. However, there has not been a lot of discussion on the possibility of applying machine learning to the process of developing a system for the use of 5G in order to improve the efficiency of such systems [21], [22], [23], [24], [25]. This is despite the fact that such an application has the potential to considerably improve the efficiency of such systems, which is something that has not been taken into account. Because of this, the current study came to the conclusion that 5G networks can support real-time monitoring of vital signs and other information connected to health, and they can also enable virtual consultations with healthcare providers. In light of this, the primary goals of this research are to discover the essential components necessary to accomplishing this.

III. RESEARCH CONCEPTUALIZATION

The basic framework of the current study is based on the extraction of the essential characteristics linked with atypical behaviors exhibited by elderly persons. These characteristics have the potential to be employed in the construction of a system that can be used for monitoring elderly people.

A. THE SOCIAL DIMENSION OF 5G ADOPTION

The social implications of adopting 5G technology are a part of the conversation that needs to happen before it can be implemented. This is absolutely necessary in order to guarantee that individuals from all walks of life will be able to benefit from 5G technology [26]. This also means ensuring that people in every part of the world have access to 5G networks and that they are able to reap their benefits. This means that the application of 5G technology to the monitoring of elderly people who exhibit odd behavior is something that should be done.

It is essential to the performance of the economy to take measures to ensure that individuals have access to the education and training they require to make responsible and profitable use of 5G technology [27]. The potential consequences that the 5G technology could have on the economy and the workforce, such as the reduction in employment opportunities that could result from increased automation, need to be analyzed as well [28]. By doing so, adopting the 5G technology might assist and ensure that people who are already at a disadvantage are not further locked out of the benefits that 5G technology offers by making the technology more generally available. Associating with a system that can monitor elderly individuals who exhibit unusual behavior is something that ought to be done, and this is also an essential part of the process.

Before rolling out 5G, it's crucial to consider the societal implications and make sure the technology will be used in a way that benefits everyone, not just a few. To put it another way, the deployment of 5G should be designed with the social dimension in mind. This dimension encompasses both the potential impact of the technology on society as well as its power to alleviate concerns that are prevalent in society. Those who live in rural areas or locations that are otherwise underserved may benefit from the potential of 5G technology to improve their connectivity [29]. In addition to the potential financial outcomes, 5G technology has the potential to enable new business models and generate new job opportunities [30].

It is necessary to keep in mind that the broad implementation of 5G could have a variety of unfavorable repercussions on society, and they must be taken into account [31]. Despite the global concerns about invasions of privacy, threats to public health, and widening socioeconomic inequality of 5G technology adoption [32], it is still necessary to associate it to the system that will be able to monitor elderly people who exhibit unusual behavior. This is ought to be done, and this is also an essential element required in enhancing the lives of elderly. If one wants to increase the likelihood that the technology will be applied in a manner that will be for the overall good of society, it is essential to address negative concerns about it through the adoption of appropriate laws and rules. Doing so will help increase the likelihood that the technology will be used. Hence It is crucial to employ 5G on a system that can monitor elderly people for any signs of unusual behavior.

B. THE SOCIAL INCLUSION DIMENSION OF 5G ADOPTION

The social inclusion aspect of 5G's adoption is what research community is talking about when discussing how it can help neglected and under connected populations [33]. When implemented, 5G technology will be able to boost connections and give people easier access to high-speed internet [2]. This could improve people's access to essential services like a system that can keep watch on older people who display strange behavior that is necessary for full participation in society. In addition to helping bridge the digital gap and expand economic opportunities for the economically disadvantaged, it can also pave the way for innovative business models and the creation of new jobs in fields of creating a system to keep checks on the elderly who display unusual behavior.

However, putting into action the benefit of 5G, it is also essential to realized how everyone may reap its benefits. Society can only succeed in this endeavor if it takes steps to prevent the disproportionate impact of this technology on vulnerable populations and expand its availability to people of all socioeconomic backgrounds and geographic locations [34]. Some ways to achieve this goal include investing in a crucial aspect of establishing a mechanism or a system to keep monitoring on older people who display unusual behavior and deploying 5G networks with consideration for the requirements of underprivileged elderly communities, and providing financial assistance to low-income startups for the development of the system for monitoring on older people.

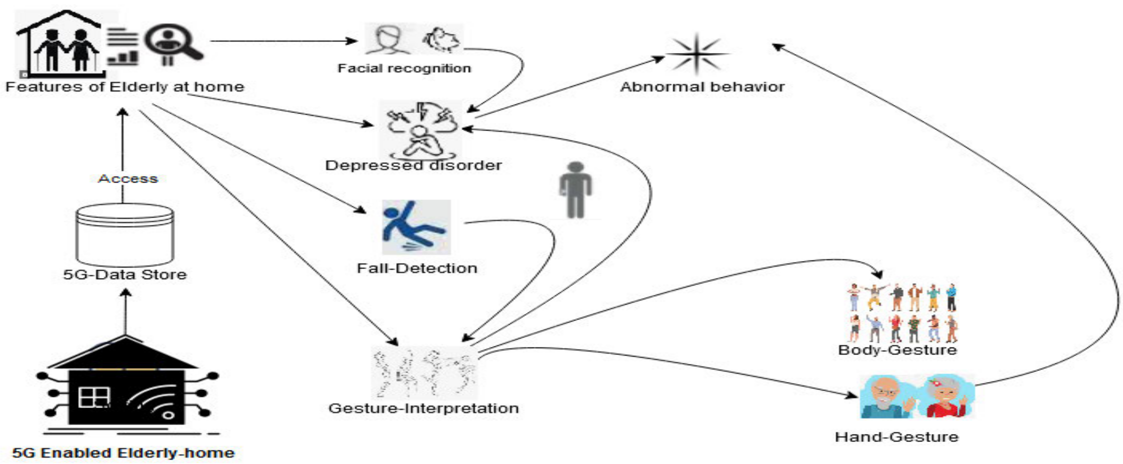

FIGURE 1. Conceptual home-based Elderly Monitoring Systems Components.

Access to high-speed internet and advanced communication services is one way that 5G technology could help marginalized communities become more integrated into society. People living in rural areas specifically the old people and those who are geographically isolated may fall into this category [35]. Access to high-quality life and cares for elderly people for the impoverished may be improved through the development of new applications and services made possible by 5G networks. This include a system to keep track of elderly persons who exhibit abnormal behavior. Not forgetting that the ability of 5G to promote social inclusion will depend on factors like the price of devices and the availability of internet connections is vital [36].

Not only elderly people, but to what extent do all members of society, regardless of their origin, socioeconomic status, or level of education, have access to and are able to utilize 5G technology is crucial [37]. To put it another way, the degree of social inclusion can be gauged by the extent to which the 5G network is utilized by all aspects of society. The focus of the present study is on the applications of the system, namely a monitoring system for the elderly. Nevertheless, the supply of the application for monitoring elderly people might not be the facilitation of the development of 5G infrastructure in places that are not currently being covered by it. However, in order for the system to be developed, it is necessary to give the necessary components. This research explains the component of elderly people that is essential for the development of the system [8], and maps it with the activities that are involved within the home that could suggest the use of the system.

Six primary criteria were identified in this research as possible explanations for the peculiar actions of the elderly. Almutari et al. [7] derived these variables from features associated with the various actions taken by the elderly. In this context, ''abnormal behavior,'' ''falls,'' ''hand gesture,'' ''face recognition,'' ''depressive condition,'' and ''body gesture'' are all relevant factors to consider. As can be seen in Figure 1, the research envisioned a 5G-enabled home for the elderly, in which the data created over the home involved all of the acts tracked over the course of time. Finding a visual picture of these processes can be as simple as watching how elderly people navigate through their daily lives. Since 5G technology permits rapid data flow from all of the many devices that are kept at home to monitor the elderly, the primary focus of the data generation is on the ability to retrieve the information quickly. This is also important since it assures that speedy deep learning models will collect and analyze the data as soon as it is generated. This is a huge benefit. This indicates that data is being generated and analyzed in the same instant that it is received.

The interaction of the common behavior that can be adopted for use in designing a system for monitoring of elderly lies with the fact that ''Features of elderly at home'' is associated to facial recognition, which can easily be used to understand whether elderly is depressed or are in a depressed disorder situation. Facial recognition is one of the main features that can be used for monitoring elderly and can be trained by ''deep learning algorithm'' in order to have a clear perception of the state of the elderly person being monitored. This is one of the main features.

The second factor is referred to as ''depressive disorder,'' and it is a condition that may be identified in senior people based on their behavior in relation to the activities they do at home. This factor stands on its own as a distinguishing characteristic. It is clear from looking at Figure 1 that although there are a number of reasons that might contribute to the diagnosis of depressive disorder, depressive illness itself is the only thing that can lead to or has a direct effect on ''abnormal conduct.'' This demonstrates that the development of a system connected with monitoring elderly people can append the problem associated with aberrant conduct, and hand gestures also demonstrate that it can lead to abnormal behavior in the elderly people being monitored. Despite the fact that fall detection is a characteristic that can only be examined by ''body'' and ''hand'' gestures simultaneously.

Taking into account the. The purpose of this study is to further investigate how this quality influences each other.

C. CONCEPTUALIZATION OF THE RESEARCH VARIABLES

Based on the fact that while gathering the requirement of the features necessary to build an application that will aid in monitoring elderly people behavior in general, in which Almutari et al. [7] provided 6 of those features to include ''Abnormal Behavior Detection (AB)'', ''Falls Detection (FD)'', ''Hand Gesture Detection (HG)'', ''Facial Recognition Detection (FR)'', ''Depressed Disorder Detection (DD)'', ''Body Gesture Detection (BG)'', from these features and assessment of their interrelations which was examined. The availability of a reliable network is one of the resources that is required to recognize older behavior. The capacity of the 5G network is extremely important, and the widespread adoption of this technology may be contingent on a number of factors that are currently unknown but that could be predicted by a deep learning algorithm. For this reason, it is essential to possess the appropriate variables that are able to carry out the function while making use of an adequate network capacity in order to ascertain the one-of-a-kind behavior of elderly people. Nevertheless, those attributes from [7] would be helpful in mapping the ''SImulated Activities of Daily Living'' acquired from Alshammari et al. [8]. Some of the common activities involve at home by the elderly that are generated in an experiment are: ''Opening and closing wardrobe'', ''Switching Television on and off'', ''opening, closing and switching oven'', ''Switching office Light on and off'', ''Opening and closing office Door Lock'' ''Opening and closing office Door'', ''walking on office Carpet'', ''Opening and closing office main Door Lock'', ''Opening and closing main Door'', ''switching living room Light on and off'', ''walking around the living room'', Switching kitchen Light on and off'', ''''Opening and closing kitchen Door Lock'', ''Opening and closing kitchen Door'', ''Walking to the kitchen'', ''switching hallway Light on and off'', ''Opening and closing fridge'', ''seating over the couch'', ''switching bedroom Light on and off'', ''Opening and closing bedroom Door Lock'', ''Opening and closing bedroom Door'', ''walking around the bedroom'', ''Switching bed Table Lamp on and off'', ''laying on a bed'', switching bathroom Light on and off'', ''Opening and closing bathroom Door Lock'', ''Opening and closing bath room Door'', ''walking around the bath room'', ''walking around the hallway''.

The word cloud of the common activities involves within the home of elderly are presented in Figure 2: In this study, significant features or key criteria from the elderly people activities at home are used. This also involve the use of 5G adoptions for a system that would be used for monitoring elderly people activities at home. Hence an analysis that merged multi-criteria decision analysis and deep learning are considered. This is due to the fact that, to begin, it is of the utmost importance to determine what essential characteristics

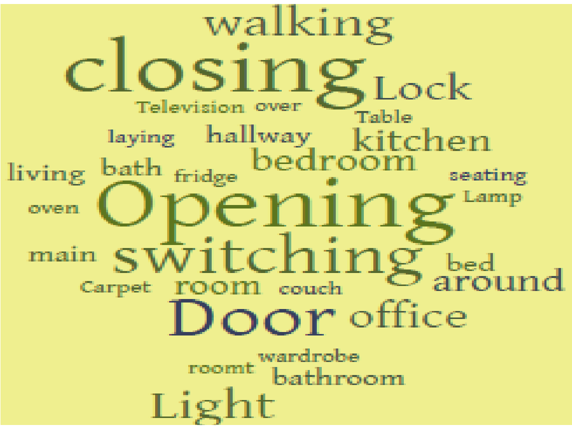

FIGURE 2. Word cloud of the Elderly Activities at home.

or criteria must be met in order for 5G to be used in a system that will be used for monitoring elderly people in their homes.

When developing assistive technology based on 5G with the intention of providing a monitoring system for older people, it is necessary to do an analysis to discover which aspects are most significant in determining whether or not this endeavor will be successful. The conceptualized elderly activities involving opening and closing doors at home associated to elderly behavior dimensions is presented in Figure 3.

In the concept, In the present investigation, a conceptual framework is developed by first charting the characteristics of geriatric behavior that are related with the action of opening and closing doors in the domestic setting. Specifically, this research focuses on the elderly. To begin, every action that has to do with opening and shutting doors has a direct bearing on ''fall detection features'' and ''abnormal or odd behavior traits.'' When it comes to spotting falls, it's easy to draw a connection between any activity involving a door opening or closing and the usage of a hand or body move. This is because door opening and closing typically include the use of both hands. With the assistance of the hand gesture recognition technology, the elderly person is able to open and close doors.

There is some degree of adaptability in the way the hand moves. The hand gesture can be used to control a variety of home appliances, including those that frequently involve opening and closing doors. The recognition of hand gestures by a computing system can provide a realistic method of engaging with any surface. This method can be linked to a computer model and used to create a programme by simply using hand gestures. In addition to allowing the elderly to point or open and close doors as needed, this method also allows the elderly to open and close doors as needed. In addition, older people who have limited mobility in their limbs can utilise the hand gesture recognition system to communicate with family members and carers, allowing them to express their needs for assistance and get it. As was mentioned by Oudah et al. [38].

In a manner not dissimilar to the previous example, shutting and unlocking doors is an example of a sort of nonverbal

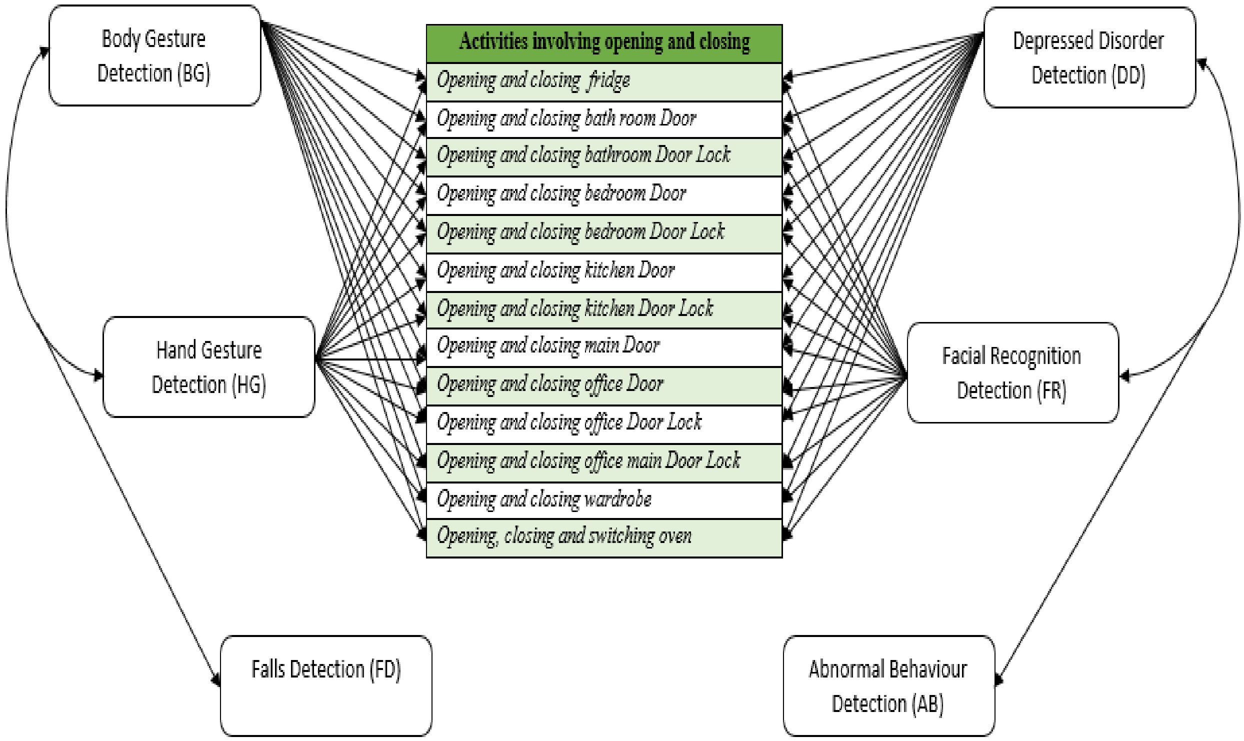

FIGURE 3. **Conceptualized Elderly Activities involving Opening and Closing Doors at home Associated to Elderly Behavior Dimensions.**

communication that carries a significant amount of weight. People are able to communicate their deepest thoughts, feelings, and beliefs to one another through a wide array of physical gestures. These gestures range from the subtle to the grandiose. This is something that is necessary in the everyday lives of the vast majority of the world's population. It is not necessary to have knowledge of any particular features in order to create a body recognition system that is capable of recognising the presence of the body of an elderly person while they go about their daily activities. This is because the creation of such a system does not require knowledge of any particular features. The same is true of gesture; in the same way that one can draw conclusions about an elderly person's behavior based on what they do, one can also analyse their gestures. There is a chance that the phenomenon known as "Fall detection" can be attributed to the effects of "Hand gesture" and "Body gesture." This is because falls are the main cause of injury among those aged 65 and older, both in terms of mortality and injuries that do not result in death. When building a system or device that can detect falls in the elderly, it is important to take into consideration the "Hand gesture" and "Body gesture" components, which are often connected with activities undertaken by persons of that age. This is due to the fact that it is essential to take into consideration these components whenever one is constructing a system or equipment. Due to this reason, the overarching objective of the conceptualization of this study is to analyse the most noteworthy features.

Another aspect of this idea is to the procedures involved in turning electrical appliances on and off. This is yet another essential concept, and it pertains to the steps that must be taken in order to turn electrical appliances on and off (see Figure 4). These pursuits are linked to every one of the Almutari et al. [7] elder behavior dimensions that were taken into consideration. These activities are connected to each and every one of the aspects of elderly behavior that were taken into consideration. It is possible to argue that this study maps all of the activities for elderly people obtained from the dataset of Alshammari et al. [8] in order to determine the impact and influence that each attribute has on another. This is something that is possible to say. This suggests that each of the six aspects of older people's behavior has a direct connection with the acts that include turning on and off the electric appliance at home. As a consequence of this, the study analyses both the interrelationships between the most crucial characteristics and the features themselves.

In addition, additional activities from the dataset collected by Alshammari et al. [8] are further conceived in order to investigate the activities that include moving about (see Figure 5). This research has demonstrated that the "Depressive disorder" and the "Abnormal conduct" component from Almutari et al. [7] are directly infusing walking activities. This concept is based on the notion of this research proposed to investigate. When this occurs, there is could be an irregular pattern of behavior as well as a depressive disorder, both of which have the potential to directly influence the activities

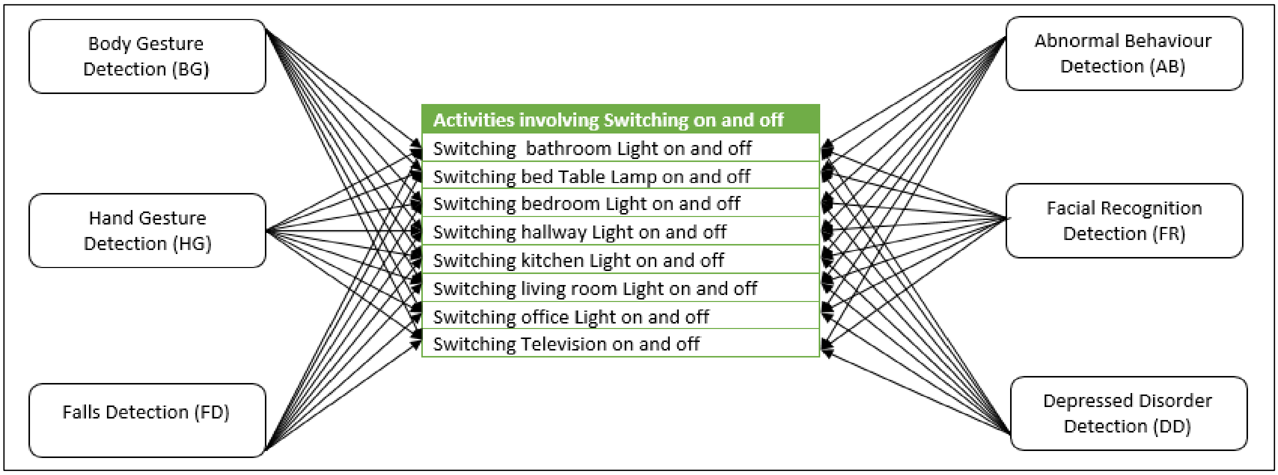

FIGURE 4. Conceptualized Elderly Activities involving Switching electrical appliance on and off at home Associated to Elderly Behavior Dimension.

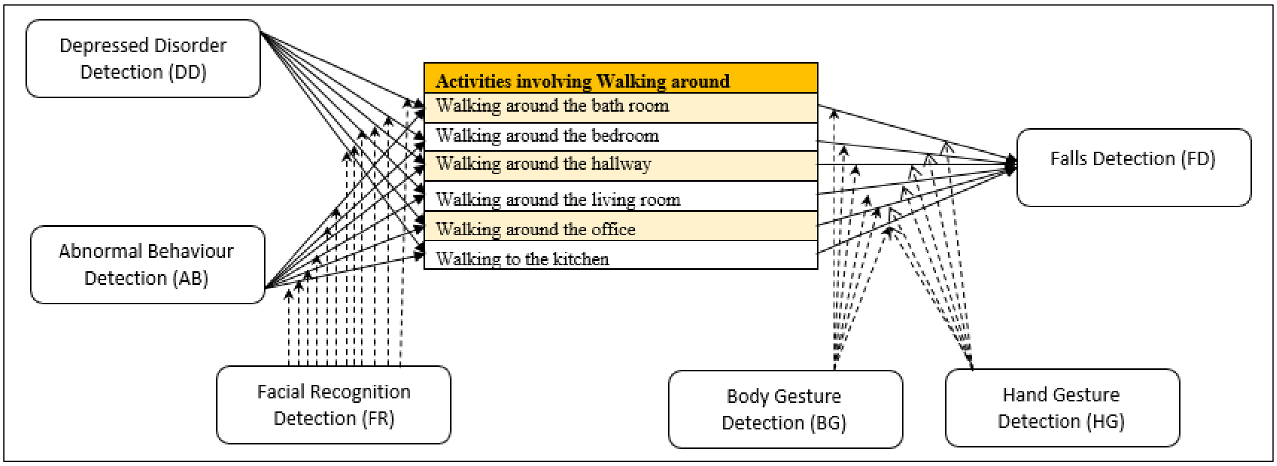

FIGURE 5. Conceptualized Elderly Activities involving Walking at home Associated to Elderly Behavior Dimension.

associated with walking or to be observed while walking. The other component that is related with this concept is the function that ''Facial recognition detection'' can play in moderating ''depressive disorder'' as well as ''abnormal behavior.'' Therefore, the effect of ''fall detection,'' which might also be moderated by ''body and hand gesture,'' is determined by the impact of these factors, which in turn determines that effect. However, the primary elements that play a role in the formation of such a notion were not understood at the time, which is why this study will investigate the formation of that concept.

The final notion is based on the findings of Alshammari et al. [8], and it focuses on the impact that activities for older persons that involve sitting or lying down can have. The mapping of these activities onto a component from Almutari et al. [7]'s research on the behavior of elderly persons provides the reason for adopting these activities. Therefore, the authors of the present study had the working hypothesis that only ''depressive disorder'' among the components from Almutari et al. [7] would be connected to the behaviors from Alshammari et al. [8] that involve sitting or lying down (see Figure 6). The influence of this idea will have a direct bearing on what is referred to as ''abnormal behavior.'' The ''Facial recognition'' component that Almutari et al. [7] developed, on the other hand, would make the concept less extreme. As a result, the other aspects of elderly people' behavior could not be mapped to the activities that involved sitting down or lying down, as the findings of this study conceptualized those activities.

IV. RESEARCH METHODOLOGY

This research focuses primarily on the social aspects of the implementation of 5G technology, with the intention of determining the component or components that have the most influence on detecting the unusual behavior of elderly people, as well as the model that is best suited to detect such components. As a consequence of this, two different methodological approaches were chosen: the ''Decision Making Trial and Evaluation Laboratory'' (DEMATEL) for the purpose of

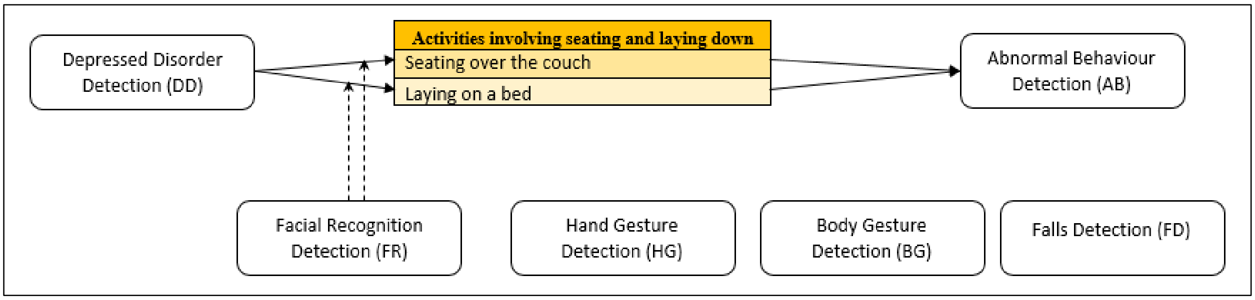

FIGURE 6. **Conceptualized Elderly Activities involving Walking at home Associated to Elderly Behavior Dimension.**

identifying the element or factors that have the most influence on detecting the behavior of elderly people, and the "Deep learning technique" as the model for the purpose of identifying the element or factors that have the most influence on detecting the behavior of elderly people.

Both of these approaches were utilized in order to arrive at the desired results. While 5G technology would be seen as the fastest means of providing real-time network operations, and deep learning would be seen as the strong technique of providing perfect prediction, the combination of these two approaches would allow for the development of a system that would assist elderly people in managing their affairs at home in an appropriate manner. This is one justification for the adoption of these two approaches. Another justification is that the adoption of these two approaches combine both subjective and experimental evaluations sequentially starting from the subjective assessments to deep learning implementation.

A. DEMATEL EVALUATION TASKS AND ANALYTICAL TECHNIQUES

There are a variety of methods available for establishing what factors contributed to the occurrence of a certain events within the activities of elderly people, which is necessary for finding the crucial key criteria that influence an event or activities of old people. The criteria for evaluation, as well as the analysis of the dataset of entire elderly people activities that was produced, present a difficulty that has to be solved. In the event that 5G is adopted for the purpose of monitoring elderly people's day-to-day activities in their homes, there will be a need to extract the real cause and effect associated with a meaningful pattern for each "cause" of an activity and its corresponding "effect" for all of the typical activities involved and their causality. This will be done in preparation for the adoption of 5G. However, the majority of the evaluation criteria for the adoption of 5G do not involve issues that are likely to have an impact on the critical situation that is currently taking place, which is either connected to the adoption of 5G in general or to its application in the monitoring of elderly people in their homes. That is why this current study adopted DEMATEL in investigating the key criteria for the adoption of 5G network technology associated to detection of elderly people behaviors.

In the evaluation phase, information is gathered by having participants (experts) use multiple-choice questions to rate how much they agree or disagree that a criterion applies to their personal experiences. The provision of multiple choice options will provide the experts more discretion in making decisions. Therefore, the research map the extracted criteria to determine the key and significance of the evaluation criteria and to learn about the relationship between them. This section of DEMATEL uses the establishment and identification of interrelationships among evaluation criteria to determine the interrelationship between cause and effect [39]. To that end, this method is used to establish the interconnections between the various indicators of evaluation. The technique ranks the different types and strengths of interactions between criteria to identify how the criteria influence one another, with the highest-ranked criterion being considered the cause criterion and the lower-ranked criterion being supposed to be the affected criterion [40]. The following procedures constitute its application:

Step 1: Planning the methods by which expert opinion will be collected: This research makes use of a questioner that was produced from the six criteria that were adopted from Almutari et al [7] and Alshammari et al. [8], and it includes multiple preferences based on the Likert scale of inter scores: 0 = "No Influence", 1 = "Low Influence", 2 = "Medium Influence", 3 = "Extreme Influence", and 4 = "High Influence" (see The appendix for the questionnaire). Fifteen sample participants are selected for this study based on DEMATEL guidelines. This can be justified by the fact that in contrast to the DEMATEL approaches, which depend on the knowledge of experts rather than statistics, the classic Structural Equation Modeling (SEM) approach necessitates a high sample size in order to establish causal correlations between components. This is because both DEMATEL approaches necessitate the participation of subject-matter experts. These techniques can determine causal relationships between variables without the huge sample sizes required by the SEM methodology [41]. The bulk of DEMATEL studies, as indicated by a survey of relevant journal articles, enlisted between 10 and 30 samples participants [42].

The purpose of the exercise was to have participants rate the criteria based on the things that made up each criterion, all of which were designed to give the expatriate more control over their own experience. As a result, x_{ij} represents how significantly participants ascribe to each criterion's impact. where i and j are the cause and effect criteria respectively. Thus for each participant's response is obtained as $n = 1, 2, 3 \ldots, n$ and an $n \times n$ non-negative direct relation matrix is form by equation 1:

$$x^y = \left[x_{ij}^y\right]_{n\times n} \tag{1}$$

where y represents the number of participation of each participant with $1 \leq y \leq q$ as a result the equation generate matrix q for x^1, x^2,... x^q where q is the number of participants. Furthermore, the average aggregated decision matrix for all the participants Z=,$\left[z_{ij}\right]$ is presented by equation 2:

$$Z_{ij} = \frac{1}{q}\sum\nolimits_{i=1}^{q} x_{ij}^y \tag{2}$$

Step 2:Constructing the normalized direct relation matrix: The normalized direct relations matrix D is generated by equation 3:

$$D = max\left(\sum\nolimits_{j=1}^{n} z_{ij}, \sum\nolimits_{i=1}^{n} z_{ij},\right)(3) \tag{3}$$

Because of this, the end effect will be that each cell in matrix Z will have a value that falls somewhere in the range [0, 1].

Step 3:Construct the total relation matrix: by raising the normalized initial direct-relation matrix D to the power of m, where m is indirect influence D^m, we obtain the total relation matrix T, which represents the total influence generated by the participant's response. Since the total relation is the sum of $D+D^2+\ldots+D^m$ hence D^m, will converge to zero, we know that the total relation matrix T is equal to the original direct-relation matrix D, then the total relation matrix T= $D+D^2+\ldots+D^\infty$ is T= $\left(D + D^2 + D^3 \ldots + D^m\right) = D\,(I - D)^{-1}$ thus

$$T = D\,(I - D)^{-1} \tag{4}$$

where I is an $n\times n$ identity matrix.

Step 4:Constructing the rows and columns of matrix: The vectors of the rows and columns that make up the complete relation matrix. If the total of the rows of matrix T and the total of the columns of matrix T are represented by the vectors r and c, respectively, then if the following holds:

$$r = [r_i]_{\mathrm{n}\times 1} = \left[\sum\nolimits_{j=1}^{n} t_{ij}\right]_{\mathrm{n}} \times 1 \tag{5}$$

$$c = [c_j]_{1\times \mathrm{n}} = \left[\sum\nolimits_{j=1}^{n} t_{ij}\right]_{1} \times \mathrm{n} \tag{6}$$

If j is equal to i then the sum of r_i and c_j will indicate the impacts that criterion i has on j, and if j is not equal to i then the sum will show the total effects given and received by criterion i while the difference will show the net effect that criterion i adds to the system. On the other hand, if it is a positive value, criterion i acts as a net cause, and if it is a negative value, it acts as a net effect. If $r_j - c_j$ is positive, then the criteria has an overall impact on the other criteria, and it can be categorized under the cause group. On the other hand, if $r_j - c_j$ is negative, then the criteria in question are being swayed by the other criteria as a whole and should be categorized as the "effect." Therefore, $r + c$ is known as the "Prominence," while $r - c$ is known as the "Relation".

Step 5:Construct a threshold value (α) to generate an interaction diagram. In order to establish a number that will decide the cutoff point for the impact relationship, equation 7 is developed.

$$\alpha = \sum_{i=1}^{n}\sum_{j=1}^{n} t_{ij} \Big/ N \tag{7}$$

where N is the total number of matrix elements that will be formed by taking the average of the members of the matrix T in order to extract any effects that are considered to be insignificant. This suggests that the impact relationships won't include any effects that are less severe than the threshold value because there won't be any.

Step 6: Generate the relationship diagram for the cause and effect: The conclusions reached as a result of the computations carried out in the preceding steps will serve as the foundation upon which the relationship diagram will be drawn. As a result, the relationship between the cause and effect has been mapped out to all of the coordinate sets that comprise the total of the rows and columns. These rows and columns show the interactions among the criteria, and they provide information that enables one to decide which criteria are the most important, as well as how the criteria influence one another.

B. DEEP LEARNING FOR UNUSUAL BEHAVIOR DETECTION OF ELDERLY PEOPLE AT HOME

The detection of unusual behavior in elderly individuals when they are at home falls within the "classification problem." This is due to the fact that the procedure involves employing a time series as a model in order to predict future values based on values or attributes that have already been seen. That is why DEMATEL was used to have a through extraction of the attribute/values required for the understanding of the detection of an unusual behavior of elderly people while they are at home. Considering the practical and theoretical implications of deep learning models, "Long Short-Term Memory (LSTM) recurrent neural networks, which have memory and can learn any temporal dependence between observations; as well as the CNN model, which has a convolutional hidden layers that operate over a one-dimensional sequence are adopted for the fact that all them are able to learn any temporal dependence between observations.

C. THE CONVOLUTIONAL NEURAL NETWORK ARCHITECTURE

This study identifies the Convolutional Neural Network (CNN) as the most well-known deep learning algorithm. It is a subset of neural networks typically employed in contexts of three dimensional units, namely the height, width and depth used for image analysis and also applies to object classification [43]. Since CNNs can learn directly from the

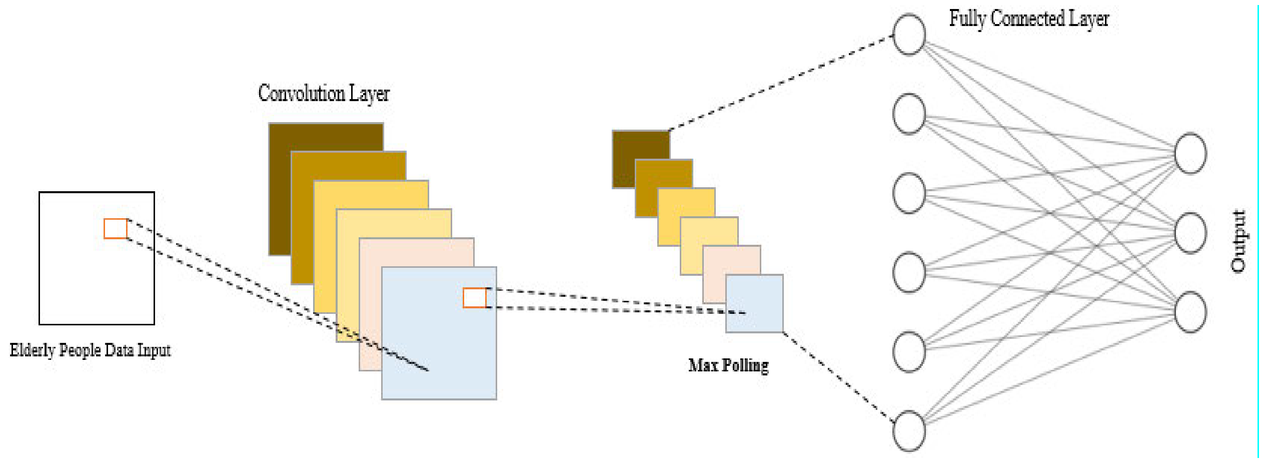

FIGURE 7. Conceptualized Elderly Activities involving Walking at home Associated to Elderly Behavior Dimension.

raw time series data, extract features from sequences of observations, and require neither domain expertise nor manually engineered input characteristics this current study plan to utilise it to detect the attributes associated to the activities of elderly people in determining their unusual behavior [44].

Input, convolution, activation, pooling, fully connected, and output are the six layers that make up the CNN's overall operational operations. A two-stage CNN approach was used in this research [45]. To begin, the research uses a feature extractor, which is a suite that can automatically extract features from raw data. The second is a fully-connected network that can be trained to perform classification using the features learned in the first step. This research uses a feature extractor to build a convolution layer, activation layer, pooling layer, and fully connected layer for a convolutional neural network (CNN). These layers need feature maps as input and output respectively (see Figure 7). After the model has been developed, it can be "fit" to the training data, and then the "fit" model may be used to generate a prediction.

D. THE LONG SHORT TERM MEMORY ARCHITECTURE

The LSTM is a recurrent neural network type that can learn order dependence in sequence prediction tasks; this is essential for solving challenging problems like machine translation, voice identification [46]. The LSTM architecture consists of three types of layers: input, LSTM (hidden), and output. The input and output layers, as well as the hidden layers, are all in continuous interaction with one another (see Figure 8). Each LSTM "layer" consists of blocks, and each block has three "gates" (input, output, and forget). To determine whether new information should be allowed in, ignored as irrelevant, or allowed to alter the output at the current time step, input gates do an evaluation (output gate) [47].

The training sample, time step, and features are the three dimensions of input data that must be molded in order to create the LSTM input layer. A new activation function was implemented in this layer (ReLu). Between the second hidden layer and the output layer, as well as between the final hidden layer and the output layer, the dropout is used in this research suggested model. The number of outputs representing various activities and anomalies are defined in the final layer (dense layer) (classes). The result is interpreted as an integer vector and then transformed into a binary matrix. The anomaly prediction problem is posed as a multi-classification issue, which in turn necessitates the generation of (number of classes) output values. The activation function is softmax, and the loss function is the category cross entropy. The evolution of the LSTM architecture is presented in Figure 8.

E. EVALUATION PERFORMANCE METRICS FOR THE DEEP LEARNING ALGORITHM

Measuring the efficacy of a deep learning is essential. The performance measurements are used to evaluate how well it performs. Different types of performance metrics reveal different aspects of the model functionality. It illustrates how a proposed technique or algorithm fares in comparison to the status quo. The performance criteria used to compare the effectiveness of the two deep learning-based model used (CNN and LSTM) are accuracy, precision and recall. All the measures are derived from a confusion matrix below:

	Detected +	Detected -
Actual +	TP	FN
Actual -	FP	TN

TP is "true positive" FP is "false positive", TN is "true negative", and FN is "false negative". Thus accuracy, precision and recall are derived by equations 8, 9 and 10, respectively.

$$Accuracy = \frac{TP + TN}{TP + TN + FP - FN} \tag{8}$$

$$Precision = \frac{TP}{TP + FP} \tag{9}$$

$$Recall = \frac{TP}{TP - FN} \tag{10}$$

The term "accuracy" refers to the degree to which a calculated or measured value agrees with an actual value or meets

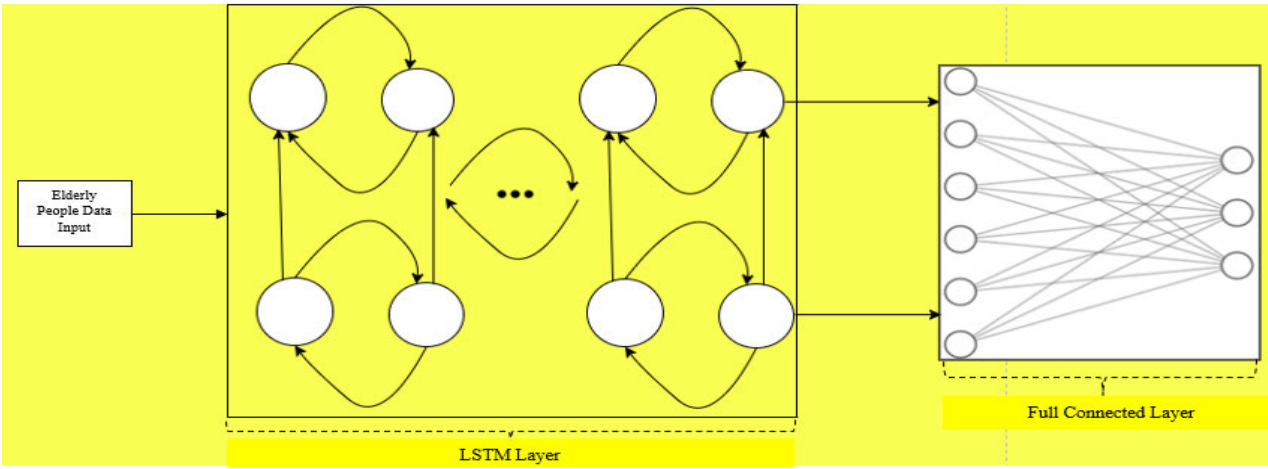

FIGURE 8. Conceptualized Elderly Activities involving Walking at home Associated to Elderly Behavior Dimension.

some other criterion. How closely experimental values match the actual value is called accuracy. The accuracy is

reported in terms of the typical error. How many True Positives did the model collect by falsely classifying them as such? (True Positive). By analogy, when the cost of a false negative is substantial, we know that Recall is the statistic we should use to choose the optimal model. When the value of a False Positive is large, precision is a useful metric to use. For instance, spotting peculiar behavior in the elderly. If an elderly person is found to be engaging in an unusual behavior when in fact they are not, this is called a false positive.

V. EXPERIMENTAL ANALYSIS AND RESENTATION OF THE RESULTS

A. DEMATEL EXPERIMENTAL ANALYSIS

The analysis of the key criteria that influence 5G Adoption for detecting unusual elderly people behaviors has been carried out by the DEMATEL approach. Following the completion of the data gathering process, the first stage in the process of obtaining the outcome of the analysis is to code the criteria and enter the data into an MS Excel sheet: "Abnormal Behavior Detection (AB)", "Falls Detection (FD)", "Hand Gesture Detection (HG)",

		AB	FD	HG	FR	DD	BG
ex1	**AB**	0	2	3	4	2	2
	FD	2	0	4	3	3	4
	HG	3	3	0	3	4	2
	FR	3	3	4	0	3	4
	DD	1	2	4	2	0	3
	BG	2	3	2	3	2	0
ex2	**AB**	0	4	3	3	2	3
	FD	4	0	3	3	3	3
	HG	3	2	0	3	3	2
	FR	4	2	3	0	4	3
	DD	2	3	3	3	0	3
	BG	4	2	2	3	2	0
ex3	**AB**	0	2	3	4	3	4
	FD	2	0	3	2	3	3
	HG	2	2	0	2	3	2
	FR	4	2	2	0	3	4
	DD	3	4	3	2	0	3
	BG	3	2	2	3	2	0
ex4	**AB**	0	4	3	3	3	2
	FD	2	0	3	2	3	4
	HG	3	3	0	3	3	2
	FR	2	2	3	0	2	4
	DD	3	4	3	3	0	4
	BG	3	4	3	4	3	0
ex5	**AB**	0	3	2	2	2	3
	FD	3	0	2	4	2	4
	HG	3	2	0	2	2	3
	FR	4	4	2	0	2	3
	DD	2	2	2	2	0	2
	BG	3	3	3	4	4	0
ex6	**AB**	0	2	3	2	2	4
	FD	2	0	2	2	2	3
	HG	2	2	0	2	2	4
	FR	2	2	2	0	2	3
	DD	3	2	3	2	0	3
	BG	4	3	3	2	4	0
ex7	**AB**	0	3	2	2	1	4
	FD	3	0	2	2	1	3
	HG	3	2	0	2	2	3
	FR	2	2	3	0	1	4
	DD	1	1	2	2	0	4
	BG	4	2	3	2	3	0
ex8	**AB**	0	2	3	4	3	3
	FD	2	0	3	4	3	2
	HG	2	3	0	2	3	3
	FR	4	4	4	0	3	2
	DD	3	3	3	3	0	2
	BG	2	2	2	4	2	0
ex9	**AB**	0	4	3	2	4	3
	FD	2	0	3	4	4	2
	HG	3	3	0	3	3	4
	FR	2	4	3	0	4	2
	DD	4	4	3	2	0	4
	BG	2	2	3	3	4	0
ex10	**AB**	0	2	3	2	4	3
	FD	2	0	2	3	3	4
	HG	2	2	0	2	2	4
	FR	2	3	2	0	3	2
	DD	2	3	2	3	0	3
	BG	3	4	4	2	2	0
ex11	**AB**	0	2	3	2	3	4
	FD	2	0	3	2	3	4
	HG	4	3	0	3	3	2
	FR	2	2	3	0	4	3
	DD	3	3	3	4	0	3
	BG	2	4	2	2	3	0
ex12	**AB**	0	3	2	3	3	4
	FD	3	0	3	2	3	3
	HG	3	3	0	3	3	2
	FR	3	2	3	0	4	4
	DD	3	4	3	4	0	3
	BG	4	3	2	2	2	0
ex13	**AB**	0	2	4	3	3	3
	FD	2	0	3	2	4	3
	HG	2	3	0	3	3	4
	FR	3	2	3	0	4	2
	DD	2	3	3	4	0	3
	BG	3	3	4	2	3	0
ex14	**AB**	0	3	2	4	2	3
	FD	3	0	3	3	3	3
	HG	4	3	0	3	3	2
	FR	4	3	2	0	2	3
	DD	2	3	3	2	0	3
	BG	4	3	2	2	2	0
ex15	**AB**	0	3	2	3	2	3
	FD	3	0	2	3	3	4
	HG	2	2	0	2	3	3
	FR	4	3	2	0	2	4
	DD	2	2	3	2	0	2
	BG	2	4	3	2	3	0

"Facial Recognition Detection (FR)", "Depressed Disorder Detection (DD)", "Body Gesture Detection (BG)". Accordingly, the fifteen experts who gave their thoughts for this study in the form of Likert scale integer scores of 0, 1, 2, 3, and 4, these are collected build into an initial individual matrix, presented in an $n \times n$ non-negative direct relation matrix using equation 1, as shown in the equation at the bottom of the previous page.

Equation 2 is used to calculate the average aggregate of the participant's decision matrices, which is also referred to as the direct influence matrix. The results of this computation are presented below:

$$Z = \begin{matrix} 0.0000 & 2.7333 & 2.7333 & 2.8667 & 2.6000 & 3.2000 \\ 2.4667 & 0.0000 & 2.7333 & 2.7333 & 2.8667 & 3.2667 \\ 2.7333 & 2.5333 & 0.0000 & 2.5333 & 2.8000 & 2.8000 \\ 3.0000 & 2.6667 & 2.7333 & 0.0000 & 2.8667 & 3.1333 \\ 2.4000 & 2.8667 & 2.8667 & 2.6667 & 0.0000 & 3.0000 \\ 3.0000 & 2.9333 & 2.6667 & 2.6667 & 2.7333 & 0.0000 \end{matrix}$$

After that, the direct influence matrix was normalized using equation 3, and the result is displayed in the following matrix:

$$D = \begin{matrix} 0.0000 & 0.1775 & 0.1775 & 0.1861 & 0.1688 & 0.2078 \\ 0.1602 & 0.0000 & 0.1775 & 0.1775 & 0.1861 & 0.2121 \\ 0.1775 & 0.1645 & 0.0000 & 0.1645 & 0.1818 & 0.1818 \\ 0.1948 & 0.1732 & 0.1775 & 0.0000 & 0.1861 & 0.2035 \\ 0.1558 & 0.1861 & 0.1861 & 0.1732 & 0.0000 & 0.1948 \\ 0.1948 & 0.1905 & 0.1732 & 0.1732 & 0.1775 & 0.0000 \end{matrix}$$

The total relation matrix refers to the total influence generated by the participant's response is determined from the normalized initial direct-relation matrix using equation 4, as shown in the equation at the bottom of the page.

Calculating the sums of the rows and columns of the matrix that constitutes the total relation matrix, i.e. the rows matrix vectors and columns matrix vectors of the total relation matrix, allows one to identify the causes and effects based on the analysis. These are found by solving equations 5 and 6. In other words, the "cause" and "effect" can be determined if the vectors r and c reflect the sum of the rows and the sum of the columns of the full relation matrix. As a result, the calculated result is displayed in the matrix above. The last evaluation establishes the relationship among the cause and the effect as indicated in section IV step 4.

TABLE 1. Direct influenced of the criteria among themselves.

	ri	*ci*	*ri+ci*	*ri-ci*	*identity*
AB	0.6713	*1.5705*	*2.2418*	*-0.8992*	*effect*
FD	0.6496	*1.4791*	*2.1288*	*-0.8295*	*effect*
H	0.6961	1.4762	*2.1723*	*-0.7802*	*effect*
FR	0.7113	1.4871	*2.1984*	*-0.7758*	*effect*
DD	0.6866	-2.7452	*-2.0586*	*3.4318*	*cause*
BG	1.5292	1.6763	*3.2055*	*-0.1471*	*effect*

In light of this, only DD was identified as belonging to the cause group (see Table 1), which meant that it had an effect on the other criteria, whilst the rest of the criteria were identified as belonging to the effect group, which meant that they were affected by the other criteria. The following step, which is necessary in order to construct an interaction diagram, is to select a cutoff value, denoted by a value (α) from the entire relation matrix. Therefore, equation 7 is used to find the value of the threshold. Because of this, the calculated threshold value comes out to be 0.1373, which indicates that any value in the total relation matrix that is greater than the threshold value has an effect on the relationships diagram. Because of this, the values in question are bolded in the matrix that can be found below:

To illustrate how the impact can connect the criteria in Table 2, an arrow is drawn from the first criterion in each row to the other criteria in the direction in which their values

I (Identity Matrix)

1	0	0	0	0	0
0	1	0	0	0	0
0	0	1	0	0	0
0	0	0	1	0	0
0	0	0	0	1	0
0	0	0	0	0	1

D(Normalized Matrix)

0.0000	0.1775	0.1775	0.1861	0.1688	0.2078
0.1602	0.0000	0.1775	0.1775	0.1861	0.2121
0.1775	0.1645	0.0000	0.1645	0.1818	0.1818
0.1948	0.1732	0.1775	0.0000	0.1861	0.2035
0.1558	0.1861	0.1861	0.1732	0.0000	0.1948
0.1948	0.1905	0.1732	0.1732	0.1775	0.0000

I-D

1.0000	-0.1775	-0.1775	-0.1861	-0.1688	-0.2078
-0.1602	1.0000	-0.1775	-0.1775	-0.1861	-0.2121
-0.1775	-0.1645	1.0000	-0.1645	-0.1818	-0.1818
-0.1948	-0.1732	-0.1775	1.0000	-0.1861	-0.2035
-0.1558	-0.1861	-0.1861	-0.1732	1.0000	-0.1948
-0.1948	-0.1905	-0.1732	-0.1732	2.8225	1.0000

Inverse(I-D)

1.1145	0.2479	0.2473	0.2581	-0.4838	0.2874
0.2491	1.0940	0.2441	0.2485	-0.4728	0.2867
0.2677	0.2424	1.1007	0.2461	-0.4336	0.2728
0.2836	0.2508	0.2534	1.1072	-0.4746	0.2910
0.2511	0.2565	0.2561	0.2508	0.3917	0.2805
-0.3486	-0.3818	-0.3936	-0.3759	-1.4473	0.4166

T(Total relation matrix)

0.1145	0.2479	0.2473	0.2581	-0.4838	0.2874
0.2491	0.0940	0.2441	0.2485	-0.4728	0.2867
0.2677	0.2424	0.1007	0.2461	-0.4336	0.2728
0.2836	0.2508	0.2534	0.1072	-0.4746	0.2910
0.2511	0.2565	0.2561	0.2508	-0.6083	0.2805
0.4046	0.3876	0.3746	0.3765	-0.2721	0.2580

T(Total relation matrix)

							Sum(r_i)
	0.1145	0.2479	0.2473	0.2581	-0.4838	0.2874	**0.6713**
	0.2491	0.0940	0.2441	0.2485	-0.4728	0.2867	**0.6496**
	0.2677	0.2424	0.1007	0.2461	-0.4336	0.2728	**0.6961**
	0.2836	0.2508	0.2534	0.1072	-0.4746	0.2910	**0.7113**
	0.2511	0.2565	0.2561	0.2508	-0.6083	0.2805	**0.6866**
	0.4046	0.3876	0.3746	0.3765	-0.2721	0.2580	**1.5292**
Sum(c_i)	**1.5705**	**1.4791**	**1.4762**	**1.4871**	**-2.7452**	**1.6763**	

TABLE 2. The values of the relationships impact.

	AB	FD	HG	FR	DD	BG
AB	*0.1145*	**0.2479**	**0.2473**	**0.2581**	-0.4838	**0.2874**
FD	**0.2491**	0.0940	**0.2441**	**0.2485**	-0.4728	**0.2867**
HG	**0.2677**	**0.2424**	0.1007	**0.2461**	-0.4336	**0.2728**
FR	**0.2836**	**0.2508**	**0.2534**	0.1072	-0.4746	**0.2910**
DD	**0.2511**	**0.2565**	**0.2561**	**0.2508**	-0.6083	**0.2805**
BG	**0.4046**	**0.3876**	**0.3746**	**0.3765**	-0.2721	**0.2580**

are greater than the threshold value. The purpose of this is to illustrate how the impact bind the attribute together. Consequently, the resulting diagraphs from this analysis are shown in Figure 9.

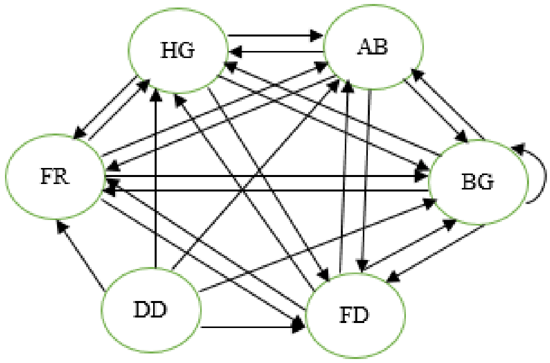

FIGURE 9. The Interrelationship Diagraph.

According to the findings of DEMATEL analysis, the ''depressive disorder'' is the key component that contributes to atypical behavior in elderly people. This conclusion was reached based on the findings of the research. On the other hand, the effects of strange behavior in older adults can be seen in terms of all of the other variables. According to the results of this study, ''depressive disorder'' does not have any influence on any of the other features that are related to this topic in any way. This suggests that the depressive condition does not have an effect on any other factors that are believed to have a connection with the peculiar conduct of aged individuals. In addition to this, it is of the utmost importance to have a crystal clear grasp of how crucial it is to measure aberrant behavior's in elderly people. As a result, the same dataset that was used in this investigation is being investigated further by means of deep learning.

B. THE DEEP LEARNING EXPERIMENTAL ANALYSIS

The ''Simulated Falls and Daily Living Activities'' dataset was taken from Alshammari et al. [8] and was the one that was used for the evaluation. These are the features of the dataset that were utilised in a previous step of the DEMATEL analysis. Despite the fact that in the DEMATEL analysis, the datasets themselves were not used; rather, the attributes of the dataset were mapped with the senior behavior dimension taken from Almutari et al. [7]. Because of this, the current study decided to conduct an experimental analysis using CNN and LSTM in order to examine the method's ability to recognise aberrant behavior shown by elderly people.

C. DATASET FOR THE ANALYSIS

This research adopted the SImulated Activities of Daily Living (SIMADL) dataset obtained by the use of OpenSHS, an open-source simulation platform, provided the freedom to generate residents' data for classification of Activities of Daily Living from Alshammari et al. [8] With the help of the OpenSHS, the research was able to use the simulated datasets with 29 columns of binary data representing the sensor results for on (1) and off (0) (See Figure 10 for the snapshot of dataset). Seven people acted out a typical day at work, at home, in the morning, and in the evening. Eighty-four files were produced, which is about equivalent to 63 days of work. A total of forty-two datasets were generated, with each participant contributing six files: twenty-four were used to simulate Activities of Daily Living classification problems using the classification dataset, and the remaining twenty-four were used to simulate anomaly detection problems using the anomaly detection dataset. During the simulation, the participants categorized their own actions. Personal, Sleep, Eat, Leisure, Work, Other, and Anomaly were some of the descriptors used by the individuals.

D. EXPERIMENTAL ANALYSIS AND PRESENTATION OF THE RESULTS

The model's capacity to spot out-of-the-ordinary behavior is crucial for this experiment's purposes. Python was used for the experiments, with the Keras library and Tensorflow being used to construct several LSTM, CNN, and Autoencoder model architectures. When working with deep learning models, there are many hyper-parameters to adjust, and doing so efficiently in a high-dimensional environment can be challenging. While some parameters may change depending on the design, others remain constant. Hyperparameters associated with Activation, the Optimizer, and the Batch size have been defined. Numerous experiments were run with various LSTM network designs and a wide variety of hyper-parameters in order to determine the best settings for the hyperparameters. Therefore, modifying the LSTM's nodes, layers, and epochs is crucial if you want to boost the model's performance. In the research, the optimum hyperparameters were established through experimentation and then utilised to create and fit the model.

The dataset can be arranged most efficiently utilising 30 nodes, 8 layers, and 10 epochs in its architecture. The framework has been tested with datasets, and the tuning of the CNN model entails adjusting the CNN hyperparameters such as the number of filters, the size of the kernel, the pooling, the number of layers, and the number of epochs. This was done in accordance with the CNN architecture that was looked at. All of these parameterizations improve the CNN's potential to have a good architecture by a great deal. The optimal

1	wardrobe	tv	oven	officeLight	officeDoorLock	officeDoor	officeCarp	office	mainDoorLock	mainDoor	livingLight	livingCarp	kitchenLight	kitchenDoorLock	kitchenDo	kitchenCarp	hallwayLight	fridge
2	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0

1	bedroomLight	bedroomDoorLock	bedroomDoor	bedroomCarp	bedTableLamp	bed	bathroomLight	bathroomDoorLock	bathroomDoor	bathroomCarp
2	0	0	0	0	0	1	0	0	0	0
3	0	0	0	1	0	1	0	0	0	0
4	0	0	0	1	0	1	0	0	0	0
5	0	0	0	1	0	0	0	0	0	0
6	0	0	0	1	0	0	0	0	0	0
7	0	0	0	1	1	0	0	0	0	0

wardrobe tv oven officeLight officeDoorLock officeDoor officeCarp office mainDoorLock mainDoor livingLight livingCarp kitchenLight kitchenDoorLock kitchenDoor kitchenCarp hallwayLight fridge couch bedroomLight bedroomDoorLock bedroom Carp bedtable Lamp bed bathroom Light bathroomDoorLock bathroomDoor bathroomCarp bedroomCarp bedTableLamp

FIGURE 10. The Snapshot of the Dataset.

architecture can be accomplished by using 82 filters, 6 kernels of varying sizes, pooling 6 layers (2,3, and 4), and 10 epochs.

The goal of the experimental inquiry that was carried out was, as was indicated in the part headed "Introduction," to detect and forecast the unique conduct. We take into consideration the accuracy, the precision, and the recall as performance measures for the various LSTM, CNN, so that we may underline the performance of the approaches that have been proposed. The results from each approach and dataset are summarized in Table 3; there are many fascinating aspects to these results. Here, the researchers examine the goal via the lens of anomaly detection, where the nature of the anomaly that is captured varies across models. For LSTM to succeed in its mission of identifying sequences of temporally abnormal behavior, it must incorporate memory cells that can store temporal dependency and information. Most importantly, deep learning may learn a hierarchical feature representation straight from the raw data, as was indicated in the "Introduction" section.

TABLE 3. The performance of the models.

	Accuracy	Precision	Recall
LSTM	96%	94%	94%
CNN	91%	89%	89%

It is abundantly obvious that the LSTM model has an advantage over the identification and prediction of temporal information. According to the metrics presented in Table 5, the LSTM model successfully captures the essential characteristics necessary to improve the accuracy of the detection of aberrant behavior. LSTM has a high level of performance, with an accuracy of 96%. In addition, precision and recall metrics were revealed by the research. On the basis of an automatic feature extraction, CNN attempts to identify sequences of time data that exhibit spatially anomalous patterns of activity. Results were achieved for the SIMADL datasets from this line of research, which involved experimenting with CNN by testing an increasing number of layers (3-CNN and 4-CNN). Even when the number of layers is increased, the performance of the model remains satisfactory. The accuracy that the CNN models were able to achieve was 91%. It was determined, on the basis of the results obtained in terms of accuracy, precision, and recall, that the model offers the most effective performance in terms of uncommon detection.

VI. DISCUSSION

The principal finding of this study lies with the following:

Highlighting the social dimension and the social inclusion dimension of 5G adoption (See section IIIA and IIIB)

- Mapping the elderly behavior components with daily home activities dataset (See section IIIB)

Revealing the key criteria for detecting an unusual behavior of elderly people (See section IVA)

Detecting an unusual behavior by deep learning (See section IVB)

While highlighting the social dimension and the social inclusion dimension of 5G adoption, the most important aspect of performing that aspect of the study is that when applying deep learning models, it is always necessary to consider computation resources required, and having the desire to take it to the next level where it is necessary to perform deep learning and deploy the result in real-time, which is why the 5G issues arise in this research. In other words, this research is being undertaken because of 5G problems. This allows the study to concentrate on determining the most significant criteria for recognizing a typical behavior shown by older adults at home in locations where 5G technology is available. This offers the study a specific focus on identifying common home-based behaviors demonstrated by elderly people.

This study, which is based on deep learning models, investigates the crucial criteria for recognizing abnormal activities carried out at home by elderly people in the context of 5G technology. It is not out of the question that one day, technology that is based on 5G networks and deep learning algorithms will have the ability to assist in the diagnosis of unusual behavior in older folks. Since 5G networks have a lower latency and a greater bandwidth, it is possible to utilize more complex algorithms and larger data sets for training and detection. This opens up a lot of new possibilities. This paves the way for an abundance of fresh opportunities and prospects. On top of that, the real-time analysis of the data obtained through in-home monitoring of the elderly can become a lot simpler to carry out with the backing of the potential for 5G to make the process easier. This is an exciting development. The execution of the analysis might be simplified as a result of this. However, the system needs to be created in such a way that it takes into consideration the preferences of the most significant criteria of senior people. This is a must. Because elderly people have additional requirements regarding their living situation and the environment in which they live, the system needs to be built in such a way that it takes into consideration the preferences that elderly people have regarding these aspects of their lives. Because of this, the authors of this study suggested that DEMATEL be used to conduct an analysis of the most essential criteria (feature) that are required when designing a model for identifying the behaviors of elderly individuals. This analysis was carried out in order to determine whether or not DEMATEL should be used. After doing exhaustive research into a variety of different deep learning models, it was found that CNN and LSTM are the models that are the most successful at spotting abnormal behavior in older individuals.

This analysis found six significant factors that may serve as potential explanations for the unique behaviors that are demonstrated by older persons. These behaviors are exhibited by people who are beyond the age of 60. These variables were derived by Almutari et al. [7] from features that are related with the different acts that are carried out by elderly persons. [Citation needed] The mapping of activities from the Alshammari et al. [8] dataset onto the ''Abnormal behavior'' dimension from the Almutari et al. [7] dataset was effective thanks to the research. Because of this, the researchers were able to conceptualise and examine the primary components that drive atypical behavior, with the intention of one-day employing deep learning to discover these qualities.

The first part of this investigation is devoted to the examination of the criteria that investigates the social ramifications of using 5G technology to keep checks on the elderly while they are at home and to control the activities they engage in on a daily basis. This entails highlighting the most essential component or qualities that can be used to develop a model that is best suited to detect unexpected behaviors. These components and characteristics can be utilized to build a model that is best suited to detect strange behaviors.

The second study focuses on studying the social consequences of utilizing 5G technology to maintain checks on children at home and to control their day-to-day activities. Specifically, the study looks at how this might affect children's privacy. The research also highlighted the relevance of integrating 5G and deep learning together as the most effective solutions for real-time operations. This was emphasized throughout the study. This was one of the most important things that I learned from doing the research. It is possible to develop a system that, when implemented for senior people, makes it simpler for them to handle their affairs at home by iteratively integrating experimental and subjective evaluations. This approach can be utilized to design the system. The findings indicate that there is a potential use for deploying technology that is based on 5G networks to monitor the social activities of elderly people while they are at home and to offer aid to those folks as they face the challenges of everyday living. has proven to be beneficial in keeping a careful eye on the health of elderly people and being ready to act promptly in the event of an emergency.

VII. CONCLUSION

5G networks and deep learning algorithms may detect ageing anomalies. 5G networks can train and identify in real time using more advanced algorithms and data sets. 5G also simplifies real-time processing of geriatric in-home monitoring data. However, the system must take into account the most significant parameters of the elderly, who have tougher living conditions and environments. Thus, this study advised using the ''Decision Making Trial and Evaluation Laboratory'' (DEMATEL) to analyse the most important criterion (feature) for constructing a model to identify abnormal behavior in the elderly. We used CNNs and LSTMs to detect anomalous elderly behavior based on a DEMATEL criteria study. The ''Decision Making Trial and Evaluation Laboratory'' (DEMATEL) and ''Deep Learning Technique'' (DLT) were chosen as the methodology models to determine the most essential component in recognising geriatric behavior. We identified the most important elderly behavior characteristics using the DEMATEL and DLT. use combined deep learning and 5G technology to provide real-time network operations. Combining subjective and experimental evaluations in a step-by-step evolution from subjective evaluations to the deep learning implementation technique of flawless prediction is another reason to use these two approaches when building a home management system for seniors. This supports studying these two ways. CNN and LSTM were used to analyze the Simulated Activities of Daily Living (SIMADL) dataset and elderly people's behavior. With 96% accuracy, the LSTM detects ageing anomalies better than previous approaches. The most influential elderly behavior feature that can induce unusual behavior is depressive disorder, as DEMATEL discovered.

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