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Sensors and Transducers for Stroke Detection: Systematic Literature Review

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ABSTRACT

Along with changes in lifestyle, stroke is not only a disease that attacks the elderly population, but also often attacks people of productive age. Actions are proposed to the public to control risk factors, such as changing lifestyle behavior or taking medication, and variations in stroke risk are tracked by evaluating stroke risk annually. The symptom of stroke that is currently widely known by the public is paralysis, even though many stroke symptoms often appear without realizing it. So it is necessary to detect stroke using sensors and transducers to detect it. The aim of this research is to examine sensors and transducers for stroke detection. This research uses a systematic literature review using Preferred Reporting Items for Systematic Reviews (PRISMA). The results of article screening and selection found 84 potential articles that met the inclusion criteria. The research results show that the development of sensors and transducers for stroke detection is currently starting to develop through artificial intelligence based on the internet of thought which uses sensors and transducers within it. Judging from the production of tools that use sensors and transducers for stroke detection. Optimization of sensors and transducers for stroke detection must be carried out with appropriate use, detailed regulatory supervision, and continuous innovation of sensors and transducers for stroke detection which is useful in reducing the number of strokes in the world.

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1. INTRODUCTION

One of the health problems in the world is stroke. Stroke has a very detrimental impact on the sufferer, the most common effects of stroke include paralysis of the limbs, facial drooping, vision problems, swallowing problems, touch sensation problems and speech problems. One of the impacts of a stroke is disruption of several human senses. Difficulty in communication will lead to self-isolation, feelings of frustration, anger, loss of self-esteem, and emotional instability in stroke patients. Stroke is the second cause of death and the third cause of disability in the world [1]. Stroke according to the World Health Organization is a condition in which rapidly developing clinical signs are found in the form of focal and global neurological deficits, which can be severe and last for 24 hours or more and/or can cause death, without any other clear cause other than vascular [2] . A stroke occurs when a blood vessel in the brain becomes blocked or ruptures, resulting in part of the brain not getting the blood supply that carries the necessary oxygen, resulting in tissue death. The prevalence of stroke according to World Stroke Organization data shows that every year there are 13.7 million new cases of stroke, and around 5.5 million deaths occur due to stroke. Approximately 70% of strokes and 87% of deaths and disabilities due to stroke occur in low and middle income countries. Over the last 15 years, on average, strokes occurred and caused more deaths in low and middle income countries compared to high income countries.

The prevalence of stroke varies in different parts of the world. Because a proper treatment for stroke has not yet been discovered, early detection is very important. By using artificial intelligence in the form of sensors and transducers for stroke detection, the development and optimization of sensors and transducers for stroke detection were studied in this research. So far, CT and MRI techniques are the most common methods for detecting stroke. However, CT and MRI are expensive and may not be suitable for developing countries or low-income communities. With stroke becoming an important disease worldwide, especially among low-income and elderly populations, health services urgently need solutions to help them detect stroke accurately and quickly at low cost. Studies on early detection and prediction of stroke are being actively conducted. The 2019 Global Burden Disease (GBD) Study estimated cardiovascular disease incidence and patient mortality in 204 countries and territories from 1990 to 2019 [3]. Based on this report, the number of deaths due to cardiovascular disease in 2019 accounted for one third of all deaths. Although the number of deaths according to the cardiovascular index increased from 11.1 million in 1990 to 18.6 million in 2019, the majority of cardiovascular disease causes are caused by ischemic stroke [4].

Detection of stroke and other brain blood vessel diseases that are widely known are CT Scan and MRI. However, CT Scans or MRI cannot assess blood flow directly and require quite a lot of time and money. Apart from CT Scans and MRIs, there are tools that use Air Pollution sensors and transducers embedded in Smartphones for early detection of stroke. In relation to electronic systems, sensors and transducers can basically be used as stroke detection tools [5]; [6]; [7]; [8]. Due to the extraordinary development of technology, almost all modern equipment has sensors in it [9]; [10]. One web-based early warning system utilizes the results of sensors, namely E-dection, which is an IoT-based prototype using machine learning methods [11]. The function of the sensor itself is to scan the energy entering the transducer [12]. In general, transducers are also often referred to as sensors [13]; [14]. This sensor is a component that is the input part of the transducer [15]; [16]. Then help him convert this energy into other amounts of energy as needed. If a transducer is a device that functions to convert energy into another form of energy [17]; [18]. It is called that because both are tools that have the same function of converting a quantity of energy into another form of energy. The transducer is mounted on another electronic device. Then the function and way of working will adapt to the function and use of the electronic device [19]. Although at first glance sensors and transducers have almost the same function and role. However, they are actually two different tools [20].

In everyday life, transducers are often used for various electronic circuits. Where the function and ability of the tool to change the amount of energy can be adjusted depending on the tool used. Because different types of devices are installed with transducers, their functions and ways of working will also be different [21]. For example, on a mic or earphone, this transducer will function to convert electrical energy into sound energy. Meanwhile, in incandescent lamps, electrical energy is converted into lighting. Previous research by Hier et al. also reported that ischemic stroke has a very high recurrence rate of 14.1% within two years [22]; [23]; [24]. Furthermore, recent research suggests a link between COVID-19 and stroke, which is expected to increase the number of stroke deaths [25] telling us that patients who are hospitalized with COVID-19 and have a history of stroke are much more likely to die than those who do not have history of stroke, [26] reported that patients with a stroke prognosis had a higher incidence of severe pneumonia and death based on Cox regression. Despite previous studies, there remains a significant lack of understanding between experimental data and data collected in real-time for stroke. Based on previous research, it appears that there has been no systematic literature review that specifically reviews sensors and transducers for stroke detection. The aim of this research is to examine the development and optimization of sensors and transducers for stroke detection.

2. METHODS

This research uses a systematic literature review method using Preferred Reporting Items for Systematic Reviews (PRISMA). Research was carried out systematically through appropriate research stages. The data provided is comprehensive, balanced and aims to synthesize relevant research results. The stages of systematic literature review research include writing the background, research objectives, formulating research questions, literature search, screening and selecting relevant articles, filtering and selecting appropriate research articles, then analyzing, synthesizing qualitative findings, and creating a research report.

3. RESULTS AND DISCUSSION

Results

Systematic literature review is a research method that aims to identify, analyze, evaluate all previous research results. The research results that have been obtained are in accordance with the research stages that have been carried out.

3.1. Formulate research questions

The results of the formulation of research questions related to sensors and transducers for stroke detection: a systematic literature review can be seen in Table 1.

Table 1. Research questions

Code	Research question	Motivation
RQ1	How is the development of sensors and transducers for stroke detection?	Identify articles related to the development of sensors and transducers for stroke detection.
RQ2	How to optimize sensors and transducers for stroke detection?	Identify articles related to the optimization of sensors and transducers for stroke detection.

3.2. Literature Search

A literature search was carried out on relevant articles using keywords, namely Detection, Sensors, Transducers, Stroke. Articles are collected from various databases, such as Scopus, Web of Science, and Researchgate (Publish or perish). The strategy used to search for articles is predetermined inclusion and exclusion criteria. This aims to ensure certainty in finding the article you are looking for.

3.3. Article Screening and Selection

Screening and selection of articles uses inclusion criteria to direct the search and selection of English language research articles, complete articles published in international journals from 2010-2023, which are indexed in a database, and have the theme of information systems for bad credit detection. The results of screening and selecting articles using the PRISMA chart obtained 140 articles from three databases, Pubmed, Web of Science, and Scopus (Figure 1). All articles (n= 140) were logged to Mendeley Desktop version 1.19.8, and articles that were duplicates, ineligible by the automation tool, and removed. Consecutively, 56 articles were excluded for various reasons mentioned in Figure 1. Ultimately, 84 articles were proposed for review in the article manuscript. The resource persons tasked with conducting the assessment are two reviewers who work independently.

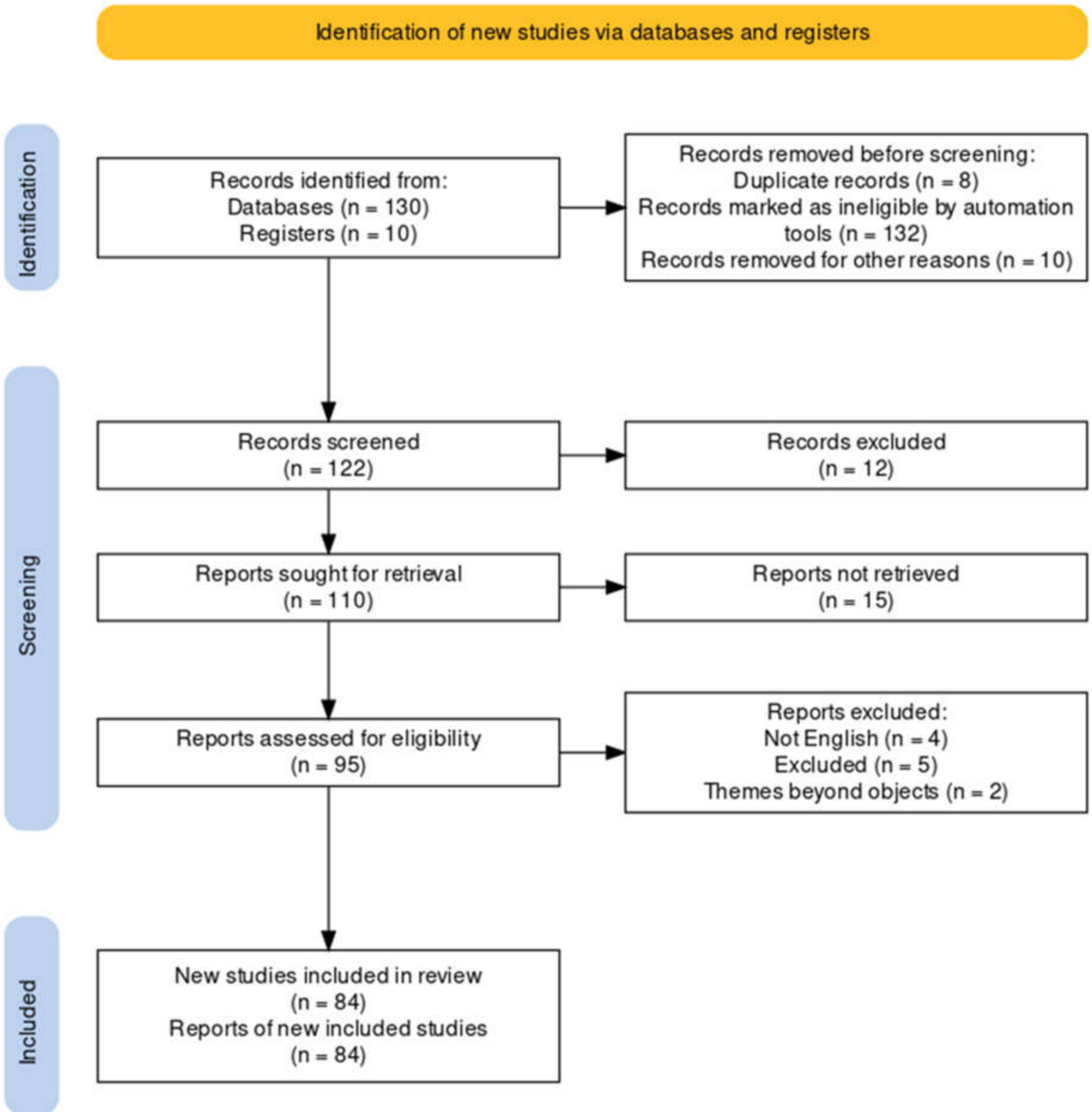

Figure 1. PRISMA chart

3.4. Data extraction, primary study quality testing, and synthesis

Data extraction aims to collect data in order to answer predetermined research questions. Research quality testing plays a role in determining the interpretation of the synthesis of findings and compiling the conclusions explained. Data synthesis aims to collect evidence from selected studies to answer research questions.

Discussion

A search for articles in three databases was successfully carried out and 140 articles were obtained. The results of article screening and selection obtained 84 potential articles that met the inclusion criteria. The theme of sensors and transducers for stroke detection was used as the theme of a new statement from the meta-analysis of 84 articles. In this theme the author discusses the development of sensors and transducers for stroke detection and optimization of sensors and transducers for stroke detection.

3.5. Development of Sensors and Transducers for Stroke Detection

An article search on three databases was successfully carried out and obtained ... articles. The results of article screening and selection obtained 84 potential articles that met the inclusion criteria. The theme of Sensors and Transducers for Stroke Detection: Systematic Literature Review was used as the theme of the new statement from the meta-analysis of 110 articles. In this theme the author discusses the development of Stroke Detection and optimization of Stroke Detection.

Starting with studying stroke. Stroke is a functional brain disorder that occurs suddenly with focal or global clinical signs that last more than 24 hours

without signs of non-vascular causes, including signs of subarachnoid hemorrhage, intracerebral hemorrhage, ischemia or cerebral infarction [27]; [28]; [29]. Meanwhile, according to [30] stroke or often called CVA (Cerebro-Vascular Accident) is a nervous function disease that occurs suddenly caused by disruption of blood flow in the brain. So a stroke is a disturbance in nerve function in the brain that occurs suddenly with rapidly developing clinical signs caused by disruption of blood flow in the brain. The classification of stroke includes [31]; [32];

- Ischemic Stroke. Ischemic stroke is a blockage of blood vessels that causes blood flow to the brain to partially or completely stop [33]. Ischemic strokes are generally caused by atherothrombosis of cerebral blood vessels, both large and small.
- Hemorrhagic Stroke. Hemorrhagic stroke is caused by bleeding within the brain tissue (called intracerebral hemorrhage or intracerebral hematon) or bleeding into the subarachnoid space, which is the narrow space between the surface of the brain and the layer of tissue that covers the brain (called subarachnoid hemorrhage) [34].

Neurological signs and symptoms that arise in stroke depend on the severity of the blood vessel disorder and its location, including [35]:

- Sudden onset of paralysis of the face or limbs (usually hemiparesis).
- Sensibility disorders in one or more limbs (hemisensory disorders).
- Sudden change in mental status (confusion, delirium, lethargy, stupor, or coma).
- Aphysia (slurred speech, lack of speech, or difficulty understanding speech).
- Dysarthria (slurred or slurred speech)
- Visual disturbances (hemianopia or monocular) or diplopia.
- Ataxia (truncal or limb).
- Vertigo, nausea and vomiting, or headache.

Risk factors for stroke include [36]; [37]; [38]; [39]; [40]; [41]; [42]; [43];[44] : a. Non-modifiable risk factors are age, gender, and family history. b. Modifiable risk factors are hypertension, smoking, dyslipidemia, diabetes mellitus, obesity, alcohol and atrial fibrillation. Thus, efforts must be made to prevent the danger of stroke immediately by detecting stroke as early as possible. Stroke detection can be done using sensors and transducers for disease detection based on the Internet of Things (IoT) [45]; [46]; [47]; [48]; [49]. One of the stroke detection methods is digital microcapillary disease [50]. This tool can measure a person's blood viscosity so that early detection of stroke is faster and ultimately it is hoped that it can reduce the number of cases and deaths due to stroke. While still in the early development stages, this tool is still very simple with one button to turn on and off. Several other components, such as the results and temperature indicators, are still made from conventional materials.

Meanwhile, in the latest development, the design of this tool is more modern and there are additional buttons with four colors. The green button functions as a heater, red to turn on (on/off) the laser, orange to on/off the screen or LCD, and blue to reload (reset). The power of this tool comes from a 9 volt capacity battery. Apart from that, the latest digital microcapillary is also equipped with a heater and the addition of three screens. The first screen is to show blood viscosity results, the second screen is to measure temperature, and the third is a voltmeter. This tool must function on 5 volt power and will not function properly if the power is insufficient. This digital microcapillary was developed with practical, easy and cheap principles. The results of measuring blood viscosity using this tool are quite fast in a matter of minutes. Another advantage is that this tool is portable so it can be used and carried anywhere, including in remote areas.

To use it, health workers only need to take the patient's blood, then put it into a capillary tube and connect it to this device. Once the laser is turned on, blood will then flow through two sensors. After a few minutes, the blood viscosity value will automatically appear on the screen. According to [51]; [52], digital microcapillaries can not only be used for stroke patients, but also people with a number of risk factors. This is because strokes can be at risk for people who are overweight, have an unbalanced diet, are smokers, are elderly, and have a history of high blood pressure and heart disease. This emphasizes that cooperation from upstream to downstream is really needed to eradicate the problem of stroke in Indonesia.

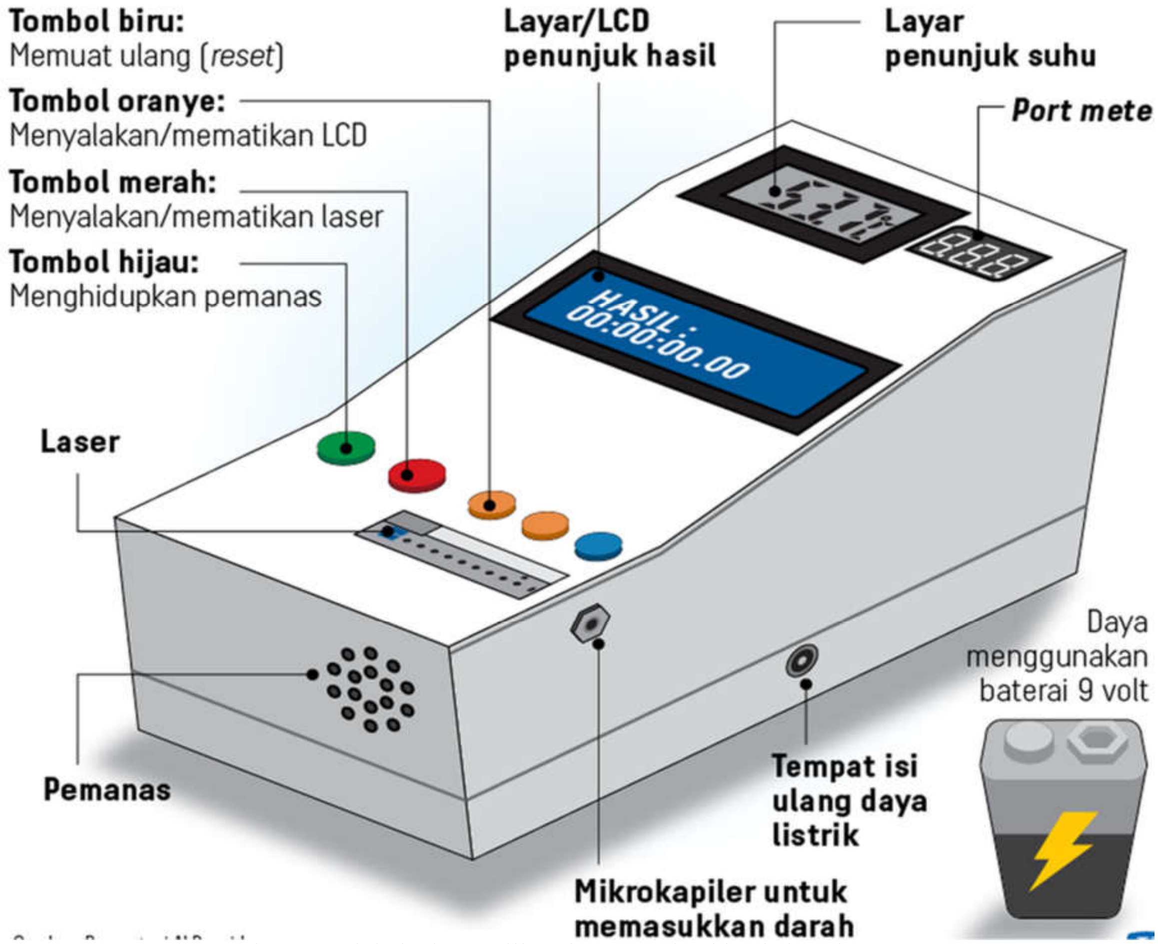

Figure 2. Digital microcapillary for measuring blood viscosity

Digital microcapillary systems are continually being developed and updated. This tool will be designed so that it can be connected online. The tool will also be connected to a computer so that blood viscosity measurement results can be read on various platforms and printed. Specifically, health facilities are expected to provide minimal facilities and infrastructure for stroke services. These facilities include the provision of imaging equipment to confirm the diagnosis, and the provision of necessary medicines for thrombolysis and improving the patient's general condition.

Apart from E-dection, which is an IoT-based prototype using machine learning methods, E-dection consists of a smart band and smart pillow which can provide monitoring functions and early independent intervention [53]; [54]. Indicators that can be monitored using E-dection are blood pressure and cholesterol and blood glucose levels non-invasively [55]; [56]. The standalone intervention used in this prototype is heat therapy to reduce the amount of cholesterol in the blood.

Figure 3. E-dection

E-dection can reduce examination costs because it is equipped with a non-invasive monitoring system and therapy to reduce cholesterol levels [57]; [58]. E-dection is an IoT-based prototype that is connected to an application. This application is useful for categorizing patient conditions using machine learning methods and makes it easier to use everyday prototypes. This innovation is expected to reduce the prevalence of morbidity and mortality caused by stroke. E-dection is an IoT-based prototype connected to an application [59]; [60]; [61]; [62]; [63]. This application is useful for categorizing patient conditions using machine learning methods and makes it easier to use everyday prototypes. This innovation is expected to reduce the prevalence of morbidity and mortality caused by stroke [64]; [65]. The increase in stroke mortality and morbidity is due to lack of monitoring and early intervention in sufferers [66]; [67].

The following are several developments in other sensors and transducers that can also be seen for stroke detection [68]:

Table 2. Development of other sensors and transducers that can also be seen for stroke detection

Development of Sensors and Transducers	Types of sensors and transducers
Sensing technology [69]	Accelerometer, Gyroscope, and Magnetometer
	Touch screen contact position sensor, touch screen contact force sensor, mechanical and optical keyboard press sensor, whole body robot skin
Sensing technology [70]	Haptic
	Computer vision, Mechanical engineering, neural networks
The technology assesses somatosensory function through interaction with the surface of the device [71]	Audio

An explanation of the development of other sensors and transducers that can also be seen for stroke detection.

3.5.1. Sensing technology

Technology that mechanically assesses body movement and gait. Sensor types: accelerometer, gyroscope and magnetometer. Contemporary wearable technology typically contains three types of very low-power motion-sensing micro-electronic engines (MEM). Triaxial accelerometers measure changes in velocity in the X, Y, and Z axes, providing information about linear displacement [75]. Triaxial gyroscopes measure rotational motion, which refers to gravitational forces [76]; [77]; [78]. A triaxial magnetometer (electronic compass) measures orientation to magnetic north. Together, these multiple motion sensing technologies provide full 9 degrees of freedom motion sensing. Compared with laboratory gold standard inertial motion units, consumer wearable MEM hardware motion detection systems have comparable performance, well within the average error limits established by the American Medical Association for reliable evaluation of movement disorders in clinical evaluation. This MEM motion sensor is able to detect various arm, trunk and leg movement disorders that occur in acute stroke [79]; [80].

3.5.2. Technology that assesses fine and gross motor interactions with device surfaces

Sensor type: touch screen contact position sensor, touch screen contact force sensor, mechanical and optical keyboard press sensor, whole body robot skin. A touch screen is an electronic visual display capable of detecting and locating touches within its display area, pinpointing the position, time, and duration of all screen contacts, with a finger, another body part, or a stylus. Structurally, a touch screen is a 2-dimensional sensing device made of 2 sheets of material separated by a spacer. Touch screens detect surface contact using one or more of several sensing technologies, of which the five most common types are: 5-Wire Resistive, Surface Capacitive, Projection Capacitive, Surface Acoustic Wave, and Infrared. With advanced implementation, touch screens can localize touch points with a spatial resolution of <0.2 mm.

Capacitive and piezoelectric pressure sensors measure the mechanical force of pressure on the surface of the touch screen. A continuous small voltage to the device layer produces a uniform electrostatic field whose disturbance can then be detected by capacitive or piezoelectric sensors, which are often placed at the 4 corners of the device surface. When a conductor, such as a human finger, contacts a surface, dynamic capacitor changes occur, with their magnitude, duration, and spatial location monitored by capacitive sensors. Capacitive coupling technology in consumer devices can detect microscopic changes in the distance between the surface and the layer of a capacitive device, enabling measurement of the pressure and motor force generated by the user. In addition to the touch screen, the keyboard is an input modality that can detect normal and abnormal motor interactions with the surface of the device. Mechanical keyboards convert the user's physical movements into electronic input with each keystroke, including capturing information about input speed in addition to semantic content. Optical keyboards use light emitters and light sensors to determine which keys are actuated, usually combining horizontal and vertical light beams for accurate detection. Optical keyboards provide better input timing information than mechanical keyboards.

Although not currently commercially available, whole surface robotic skin is an additional sensor technology under development that could improve the automated detection of patients' fine and gross motor deficits [81]; [82]; [83]. Covering the robot's entire surface with tiny sensors that can measure local pressure and transmit data over a network provides an artificial skin on the robot to improve the robot's sensory discrimination, actions, and safety. In addition to improving the robot's interaction with inanimate objects, the entire surface of the robot's skin will improve the robot's detection of abnormal touches by interacting humans. Wafer bonding technology for integrating capacitive force sensors using silicon diaphragms has been shown to increase the need for packaging force sensors in small volumes.

3.5.3. The technology assesses somatosensory function through interaction with the surface of the device

Sensor type: haptic sensor, Haptic touchscreen technology creates a user experience in touching various types of surfaces by applying feedback force, vibration, or movement to the user when the touch occurs [84]; [85]; [86]. Depending on how much force is applied to the surface of the device, the haptic is able to respond with appropriate feedback that creates the sensation of clicks, vibrations, and rising or falling surface contours. The three most common types of haptics are Eccentric Rotating Mass (ERM), Linear Resonant Actuator (LRA), and Piezo Haptics. The electromagnetic linear actuator is capable of reaching peak output in just one cycle and produces vibrations that last for 10 milliseconds. Unlike most motors, linear actuators do not rotate but oscillate back and forth. Multiple actuators are mechanically connected to the back of the input surface, distributed along the surface, each at a separate contact location, to provide local haptic feedback to the user. Small robotic devices have been developed that are capable of assessing various patient somatosensory functions by generating standardized sensory stimuli directed to various parts of the body.

The Robotic Sensory Trainer Device assesses, and rehabilitates, tactile function. In the assessment, the device provides finger use with well-controlled amplitudes of angular displacement, vibration and surface pressure, while recording the user's position and perception via a touch screen [87]; [88]. The H-Man robot uses a 2 degrees of freedom planar robot to quantitatively describe proprioceptive deficits in post-stroke patients. This technology can be easily added to existing, commercially marketed home health robots, and with further miniaturization and adaptation, it can also be applied to smartphones and smartwatches [89].

3.5.4. The technology assesses motor function through computer vision

Sensor type: computer vision, Mechanical engineering, neural networks, and deep learning have led to dramatic advances in computer vision functionality over the past 20 years. Methods for acquiring, processing, analyzing scenes and individuals, and extracting high-dimensional data from the real world have proliferated. The sub-domains include object recognition, face recognition, scene reconstruction, event detection, video tracking, 3D pose estimation, learning, indexing, motion estimation, and 3D scene modeling. Visual recognition systems have been incorporated into smartphones (including facial recognition to unlock the phone), smart watches, smart cars, smart robots, and closed-circuit television systems [90]. Community surveillance using CCTV is common in many regions of the world and allows the detection of stroke symptoms arising in everyday life over a wide geographical area [91].

3.5.5. The technology assesses voice and language through audio sensors

Sensor type: audio, The smart speaker combination is a voice command and speaker device with an integrated artificial intelligence virtual assistant that enables interactive actions and hands-free activation with the help of trigger words. They usually audit the sound environment continuously while connected to electricity. Most modern general-purpose speech recognition systems use hidden Markov models or deep learning computational linguistics to perform acoustic modeling and language modeling [92]; [93]; [94]; [95]. The accuracy of speech recognition in consumer systems has continued to improve over the last decade [96]. In 2019, in response to user questions, the best performing systems attempted to answer 80-85% of utterances and provided complete and correct answers to 72-82%.

As the sophistication of modeling and analysis and decoding of normal speech increases, speech recognition systems also develop increasing capacities for identifying abnormal acoustic (phonemic), linguistic (semantic), and paralinguistic (prosodic) output [97]. The role of a transducer can be seen from emitting sound waves and recording the echoes when the waves bounce off tissues, organs and blood cells. The computer translates the echoed sound waves into live-action images on the monitor. During an ultrasound, the ultrasound technician may use a Doppler ultrasound, which shows blood flowing through the arteries. In Doppler ultrasound, the blood flow rate is translated into a graph. There have been rapid technological advances in carotid ultrasound, which are improving image quality and resolution. A carotid ultrasound usually takes about 30 minutes. Of all the developments in sensors and transducers for stroke detection, it can be seen that they are becoming more advanced from year to year in order to reduce the number of stroke sufferers [98]; [99].

3.6. Optimization of sensors and transducers for stroke detection

To overcome obstacles in dealing with sensors and transducers for stroke detection, the following things are done:

3.6.1. Extending current detection device use cases to scratch settings

Although the ability of motion-sensing micro-electronic machines to detect falls due to stroke is now well proven, extrapolation of other technologies to stroke requires proof-of-concept demonstrations. For example, computer vision's ability to identify strabismus and phoria needs to be extended to stroke-related gaze deviations and computer vision detection of peripheral facial weakness needs to be extended to stroke-related central facial weakness [100].

3.6.2. Achieving sufficient specificity and sensitivity for useful applications

Given the variability in normal human activity, there is great potential for devices to mistake non-stroke events for stroke events. For example, alcohol poisoning is likely a more common cause of dysarthria and language changes than stroke, and speech detection algorithms must be very reliable in distinguishing these to avoid too frequent false alarms and notifications.

3.6.3. Determine the best strategy for linking automated stroke symptom detection with automated help notifications

As with existing fall detection technology, its use could set the device to contact family members, friends, doctors, human-supervised security companies, and operators. The best linkage approach will likely vary based on the type of symptom detected, response resources available in a region, and individual user preferences [101].

3.6.4. Reduce excess data

A formidable challenge for the successful application of mobile technology for stroke detection is ensuring the usability and readability of the data for providers and patients [102]; [103]; [104]; [105]. Large amounts of data that can potentially be analyzed in real-time require appropriate sampling and clinical frameworks to achieve actionable clinical relevance.

For sensor technology to be widely used, patients must be assured of the privacy and security of their data [106]; [107]; [108]; [109]. Detailed regulatory oversight is required. To facilitate rather than slow innovation, the U.S. Food and Drug Administration and the Federal Communications Commission have adopted a risk-based approach to regulatory oversight, focusing on aspects of device performance that could compromise patient safety if they do not function as intended, but have not addressed those issues. privacy and ownership of Health data [110]. Health information privacy laws already exist in many countries, but need to be refined to cover the large data sets that sensor technologies acquire in normal living environments.

4. CONCLUSION

Stroke is a frightening disease as the number 1 cause of disability and number 3 deadly disease in the world. It not only attacks the elderly but also attacks the productive age. One thing that must be done to reduce the death rate due to stroke is early detection of stroke. Development and optimization of sensors and transducers for web-based stroke detection that utilizes the results of sensors and transducers. IoT-based applications that use machine learning methods can help overcome the problem of increasingly high stroke rates.

DECLARATION

Author Contribution

This research uses a systematic literature review method using Preferred Reporting Items for Systematic Reviews (PRISMA).

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Conflict of Interest

Declare conflicts of interest or state “The authors declare no conflict of interest.”

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