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ESTIMATION OF PROXIMITY, PRESSURE, CONDUCTIVITY, AND TEMPERATURE FOR A COMPUTER-AIDED DESIGN AND DEVELOPMENT OF BIONIC HAND TO BE USED BY ROBOTICS AND AMPUTEES: A SYSTEMATIC REVIEW

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Abstract
This study aims to review state of the art for dexterous robot hands, also referred to as multi-fingered prosthetic hands. Making an artificial hand resembling a human hand has always captured people's attention. Mimicking a human hand remains one of the most challenging robotics projects, requiring enormous efforts based on multidisciplinary techniques that vary from design to neuroscience. This study summarises artificial hands created in the past and present for humanoid robotics and prosthetics research initiatives. The estimation of proximity, pressure, conductivity, and temperature can be achieved through various sensors and algorithms, which will enable the bionic hand to mimic human-like behavior. This paper discusses the different techniques used for estimating proximity, pressure, conductivity, and temperature, and how they can be integrated into the CAD process. The paper also highlights the challenges associated with the development of bionic hands and how the estimation of these parameters can help overcome these challenges. To develop a simple, competent, and functional bionic hand, two major requirements must be met: sensing capability and (ii) the capacity to hold objects stably and securely. This paper begins by reviewing the existing literature on the various performance criteria used for prosthetic hands. Additionally, the existing pressure, temperature, and proximity of prosthetic hands are examined. Relevant articles published between 2006 and 2022 were searched for this purpose, and 75 papers were chosen and assessed based on the performance criteria. Finally, based on its intended use, this study indicates some important aspects of developing a robotic hand.

1. INTRODUCTION

A robot hand is needed for carrying out various tasks in everyday life and is designed to perform tasks whenever required, particularly for repetitive and dangerous tasks, as well as military functions robots and automation The hands are a body part that performs an important role in everyday activities. Hands are one of the human body's 19 bones, 24 muscles, veins, and sensory, motor, and neural networks [1]. People who are disabled will benefit from the bionic hand we will develop. Making a correct choice, the gripping in

the robotic hand can execute functions such as carrying out and positioning the object. Bionic hands have significant advantages for people who have lost or were born without a limb as they can improve their quality of life and increase their independence. Bionic hands can provide a greater range of motion and dexterity compared to traditional prosthetic hands, enabling individuals to perform more complex tasks and activities and can be designed to mimic the natural movements of the human hand and block diagram show in figure 1 , providing a more realistic and comfortable experience for users. Some bionic hands can give the user sensory feedback, allowing them to sense pressure, temperature, and even touch, which can improve their ability to perform tasks and interact with their surroundings [2-33]. The development of bionic prosthetic limbs is accelerating. Only a small number of individuals operating in highly specialized units are presently required to have in-depth knowledge of this field of medicine. However, as technology advances, it is likely that the desire for and application of bionic hands will grow, necessitating a broader understanding [34]. Pressure sensors in bionic hands provide sensory feedback to the user, enabling them to feel the pressure and texture of items being held and sensors attach with the hand shown in figure 2. For example, this may enhance the user's skill in handling fragile objects. Pressure sensors can also ensure the user's safety by sensing excessive force or pressure applied to the bionic hand [35-53]. This can help to avoid device damage or user injury. High-performance pressure sensors are typically used in robotics, aerospace, industrial, biomedical, environmental monitoring, consumer, and portable electronics applications.[54]. Capacitive sensors can halt the entry process and record the force exerted by a step. This lets bionic hand grab. A proximity capacitive sensor detects an object up to 100 mm distant with a maximum to 12 N touching energy. This allows the operation space and maximum force load of the prosthetic hand's fingers to be determined [55-94]. Also, sensor had great steadiness, mechanical flexibility, and the ability to change shape [95]. The prosthetic hand is capable of identifying the temperature and pressure of objects that are being grasped automatically. The use of a prosthetic hand can increase user happiness and advance humanistic care for persons with disabilities.[96].

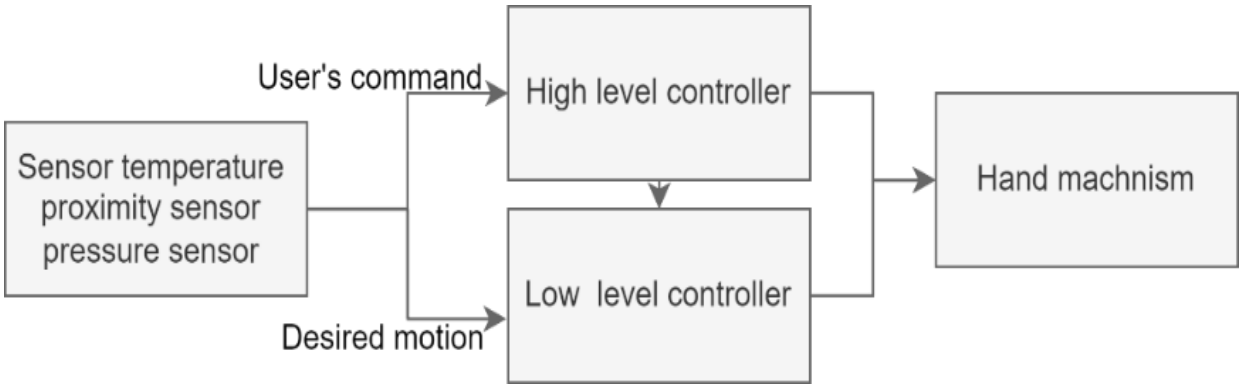


Figure 1: Bionic hand control block diagram

In the area of robotic grasping, one problem being studied is predicting the stability of a grip. To find a solution, tactile sensors are the main data source since they offer useful details (such as temperature and pressure) regarding the forces at work when the robotic hand interacts with objects. Two states are commonly separated in terms of stability prediction: stable, which indicates that the object is securely gripped, and slippery, which denotes that the object may slide from the hand. [97]. As bionic hands have significant potential advantages, some limitations and challenges must be addressed in their design and development. Bionic hands can be costly to develop and make, limiting their availability and accessibility to those in need. Bionic hands are

intricate devices with numerous moving components. While bionic hands can provide a more extensive range of motion and functionality, users may need help to control them. They may need to undergo significant training to learn how to operate the device effectively, and bionic hands represent a substantial advancement in prosthetic technology. Still, limitations and challenges need to be addressed in their design and development to make them more accessible, functional, and user-friendly.

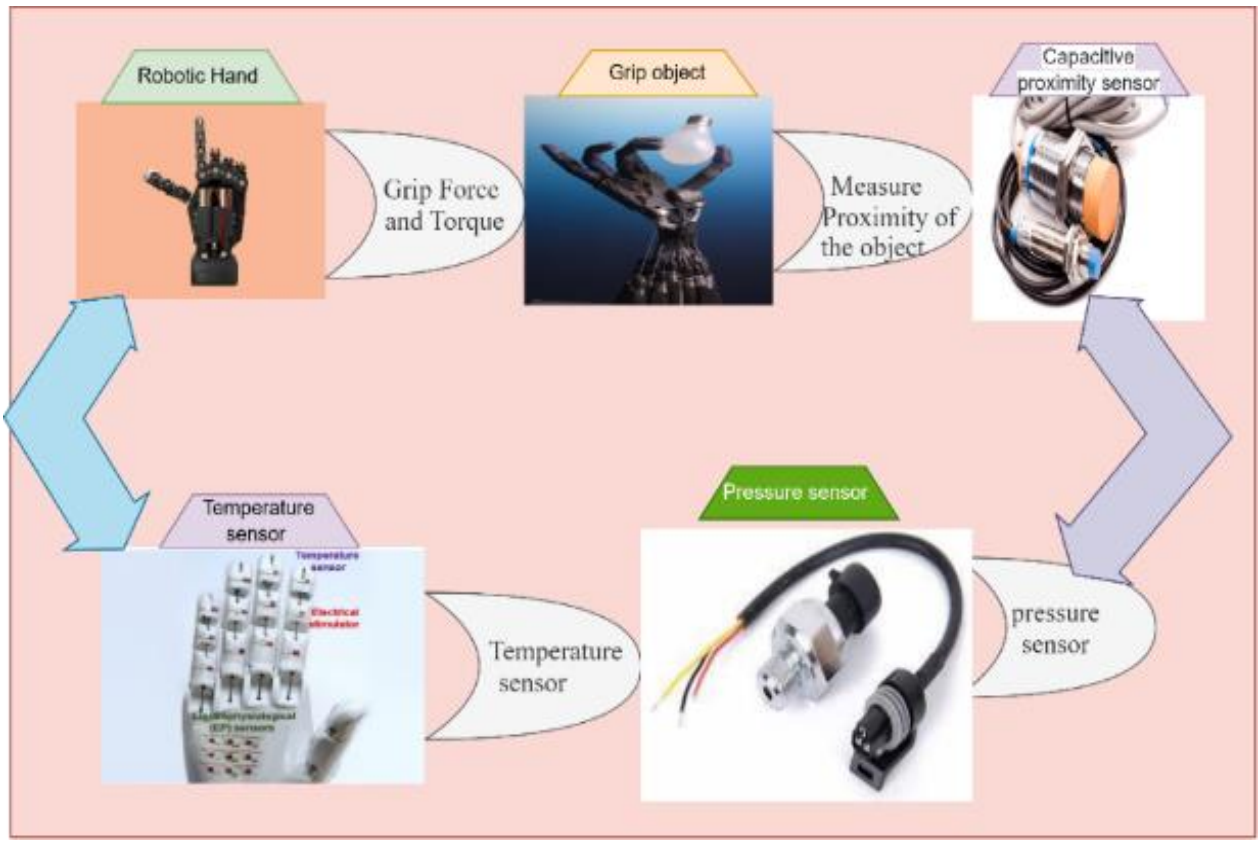


Figure 2: Prosthetic hand design for proximity and temperature detection, as well as grip and force

1.1. Pressure sensing in the prosthetic hand

In the prosthetic hand, pressure sensing is crucial for holding, grasping, pushing, and pulling objects. Consequently, five pressure sensors were attached to each fingertip and one sensor was glued to the hand's palm and the segment of the bionic hand shown in figure 3. As sensor technology has advanced, prosthetic hand applications have utilised various sensors. One of these sensors is a piezoresistive Flexi Force sensor, which employs the resistive technique with resistance that is inversely proportional to the applied force, as demonstrated by Equation 1[98].

$$P = \frac{F}{A} \quad (1)$$

Where P denotes the pressure F denotes the applied force, and A denotes the area of the surface to be contacted .

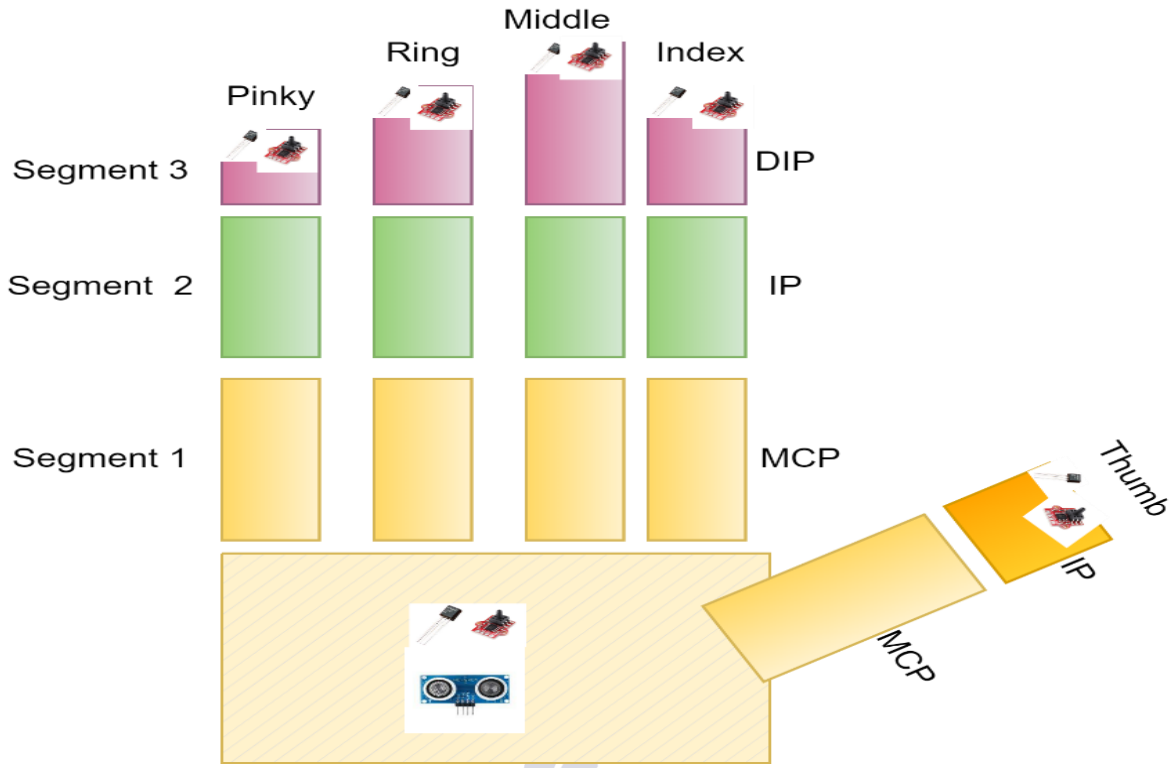


Figure 3: Bionic hand segments

1.2. Temperature sensing in the prosthetic hand

Temperature sensors are essential in designing and developing bionic hands since they can provide helpful input to the user and aid in improving the device's performance. Temperature sensors can offer feedback to the user regarding the temperature of their surroundings, which is especially valuable for people who may have diminished sensitivity to temperature due to an injury or amputation. Temperature sensors can also be used to determine the temperature of objects handled by the bionic hand, which is beneficial for tasks requiring a delicate touch, such as cooking or taking hot or cold things. Amputees' daily activities are restricted by the prosthetic hands' lack of temperature perception. A fundamental physical variable that is a significant predictor in a variety of applications is temperature. The resistance temperature coefficient (TCR) describes the temperature-sensitive property shown in equation 2.

$$\text{TCR} = \frac{(R-R0)}{R0-\Delta T} \quad (2)$$

R, R0, ΔT is the resistance

1.3. Proximity sensor

Proximity sensors are a crucial component in the design and development of bionic hands since they can help to improve the device's functioning and safety. Proximity sensors can detect the presence of objects in the surroundings, which is essential for jobs requiring the user to maneuver around barriers or avoid collisions. Environmental feedback, safety, and user involvement are all provided via proximity sensors. Proximity sensors are a crucial component in designing and developing bionic hands because they provide valuable feedback and control, which can improve the user's ability to accomplish activities and overall experience with the device.

The purpose of this review is to provide a review of the most significant advances in bionic hand technology over the last few years, with a focus on using various techniques for measuring force, pressure, and temperature, as shown in figure 4.

This research analyzes numerous techniques for creating bionic hands, such as artificial neural networks, the Fast Fourier Transform (FFT) method, the Multi-layer Perceptron method (MLP), finite element analysis (FEA), CNN-LSTM, training data, and decodes algorithms, semi-autonomous bionic hand, Pneumatic Artificial Muscles (PAM), and the CAD model. This study also investigates the various sensors used in various studies. The paper discusses flex force sensors that have been used in previous studies. The substrate of the Flexiforce sensor is manufactured from a high-quality polymer, which enhances the force, linearity, hysteresis, drift, and temperature sensor performance, with the maximum, selected temperature of 48 °C to investigate the effect of discomfort on learning quality.. Furthermore, this study looks at an autonomous machine controller that can autonomously controlling each finger with a sensor by optimizing proximity (getting closer to the thing being detected) and using grip force and temperature sensors, EMG, and EEG sensors used in previous studies. In summary, as shown in Table 1, applications for tactile pressure sensing, temperature sensing, and proximity demonstrate a considerable rise in publications and research attention. As a result, to address the issues, the sensor's design is improved to be more precise and reliable.

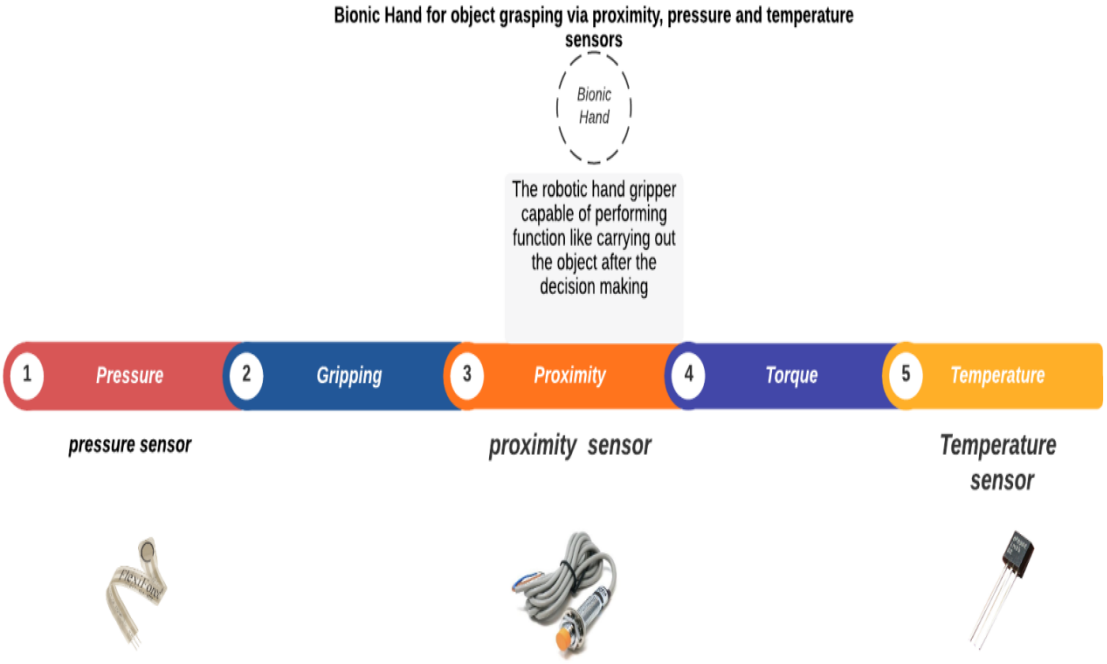


Figure 4: Categories of the study according to the sensors

A bibliometric analysis of published papers from the Scopus database was carried out. We reviewed published papers from 2011 to 2022 using the keywords "bionic hand," "grip force," "pressure sensor," "proximity sensor," and "temperature sensor," as shown in figure 5 (a). The majority of the papers were published in the journal category. Figure 5 (b) depicts the annual publications from 2006 to 2022. (C) displays country-specific publications; the top five countries are the United States, China, Italy, Malaysia, and Belgium. Figure 5 (d) also displays the publications by subject area.

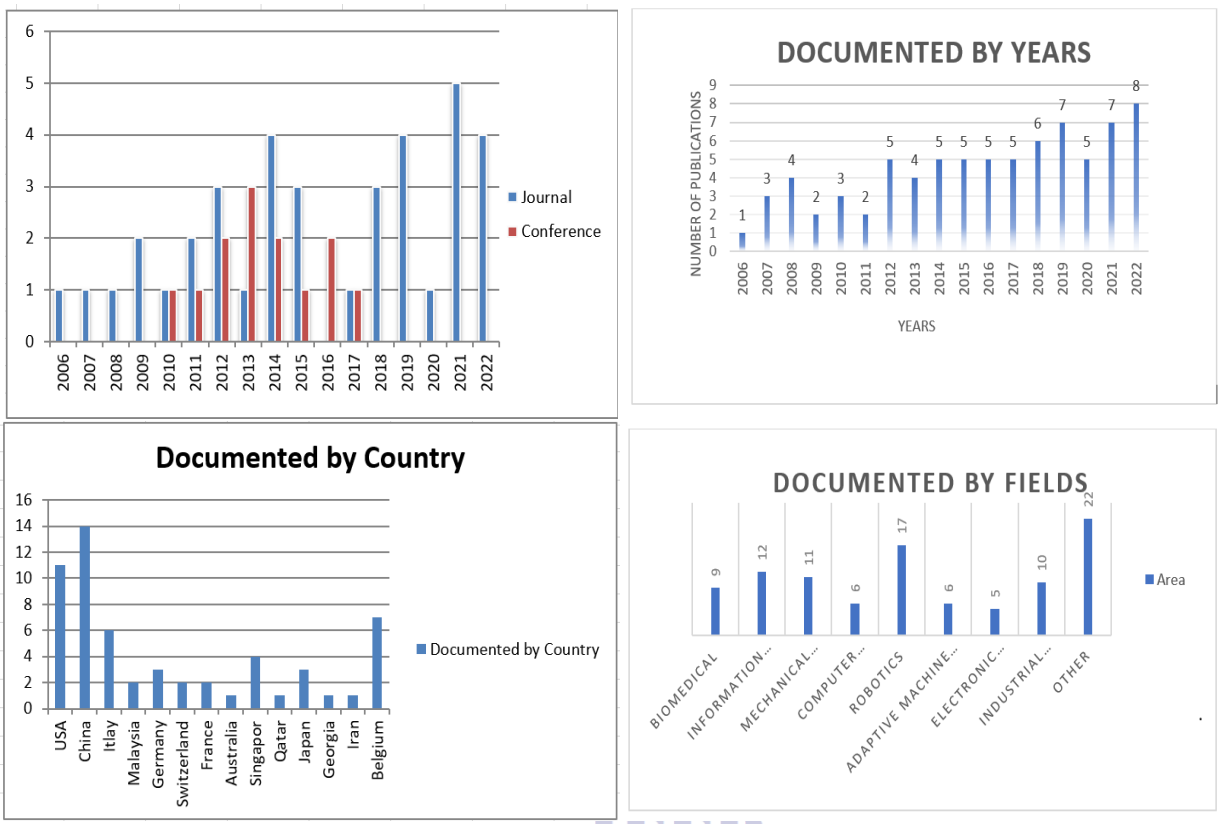


Figure 5: (a) papers by journal + conference; (b) papers by year (2006-2022); (c) paper by country; (d) paper by subject area

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1.4. Organization of this study

The remaining portions of this study are organized as follows: Section 2 describes how this study differs from other survey papers. Section 3 goes into detail about bionic hand approaches. Sections 4 and 5 go over the state of the art, techniques, tools/equipment used, comparison, and limitations. Section 6 concludes the analysis by highlighting the challenges. Section 7 discusses future directions, and Section 8 ends this review. This search for review articles resulted to 244 publications, 166 journals, and 78 conferences, of which 91 were from IEEE, 52 from Springer, 48 from Elsevier, and 3 from other publishers. Finally, 78 studies were included in this review as shown in figure 6.

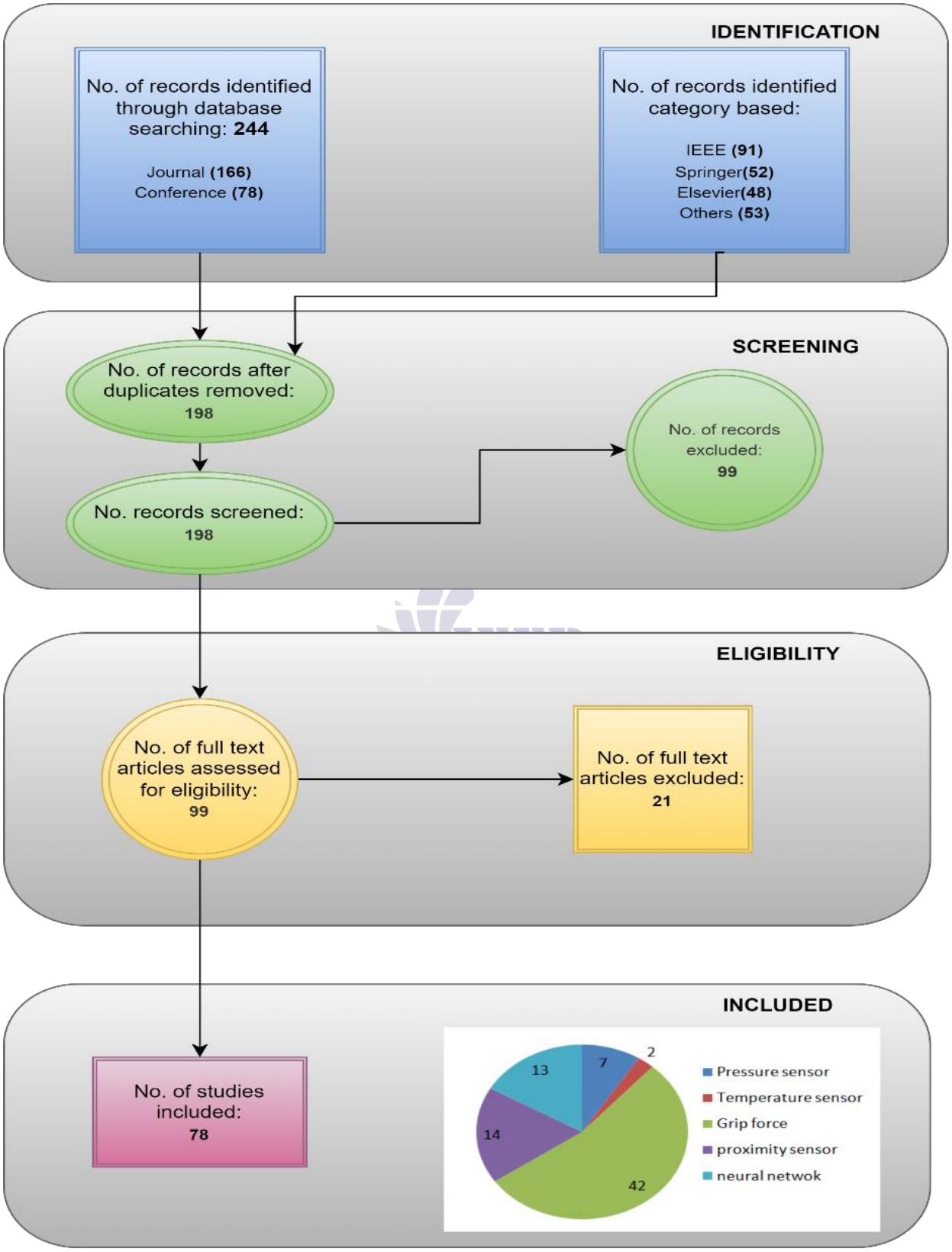


Figure 6: Overview of research articles

Overview of research papers of bionic prosthetic leg published in different journal, conference and publisher wise, shown in figure 7.

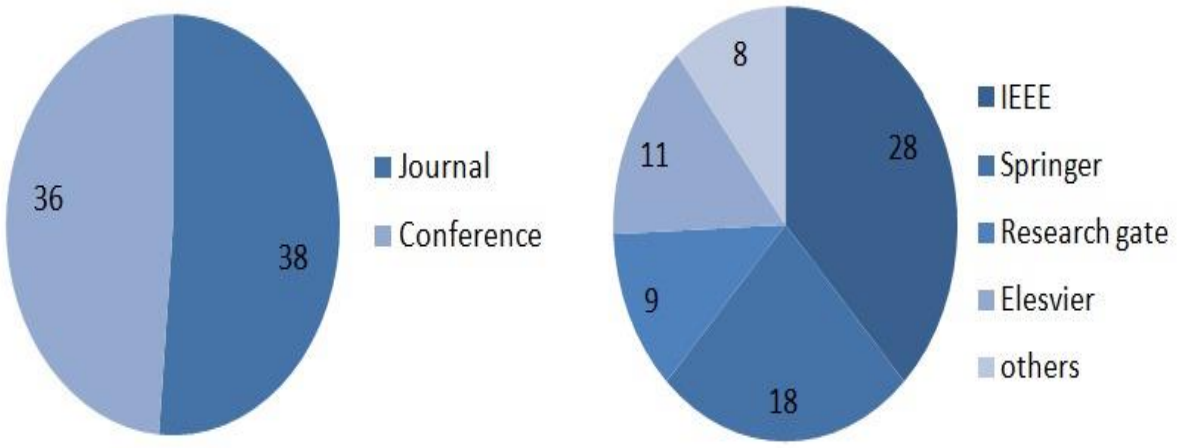


Figure 7: Overview of research papers of bionic prosthetic leg (a) journals and conference paper (b) publisher paper

2. Literature review

In this article [99], the author purposed a semi-autonomous bionic hand using Proximity, fingertip, and Pressure Sensors that may help a person with complicated tasks in a synergistic way. During individual fragile-object trials, the fingertip sensors offered a rich dataset to assess proximity and pressure values. Although machine control greatly exceeded human control, it was made to function with delicate items, which limits the current investigation. All subjects and task difficulties were successful in trials completed with the native hand.

A versatile flexible artificial hand with a Nanoscale temperature and pressure sensor is designed to recognize objects. [100]. This flexible multifunctional tactile sensor can measure the rate of temperature change and pressure on contacts. Its functionality is attributed to integrating a nanowire-based temperature sensor and a conductive sponge pressure sensor. Soft finger's high accuracy level in material discrimination results from a combination of tactile input and artificial neural networks.

Another article [95], uses a single, monolithically integrated capacitive sensor for proximity and pressure sensing. Objects within 100 mm of the top electrode are greatly affected by the fluctuating fringing electric field generated by the ring's shape. However, gradually modifying the microstructure between the two electrodes makes a sympathetic force range of up to 12 N possible. Gripping control on the prosthetic hand is achieved by employing capacity sensors interrupting an incoming process and recording a step force. Due to the small finger size, the sensor can only be 3 mm in diameter.

This study [101], Develops sophisticated robotic technologies, such as adaptive grasping, biomimetic robots, and human-machine interfaces. In addition, it offers a novel method for developing functional pressure sensors. The PC-mechanical gel's so state compressive modulus is 300 kappa, but its rigid state compressive modulus is over 600 times higher. Depending on the compliance and modulus of the target items, the robotic gripper can be modified to grasp small, light objects with high sensitivity or large, weighty objects with low sensitivity.

In this study [102], design a bionic prosthetic hand system with two closed-loop control loops to facilitate adaptive grasping using a linear discriminate analysis (LDA) algorithm. A linear servomotor powers each of the five digits on the prosthetic hand. The linear servomotor stretches and bends the thumb, whereas the other four digits automatically adapt and turn according to the appropriate gripping gesture. As is common

knowledge, the overlapping radio responds more quickly the higher it is. However, it should not be assumed that we should set it as high as we can. As a result, it can attain an average accuracy of 96.59%.

In this article [103], the author proposes a distributed contact force and tactile information detection method for multi-fingered robotic grasping applications. Six distinct grasping modes are selected for dexterous robotic grasping, and object-grasping experiments are conducted. In future research, the behaviour of tactile forces during various grasping motions will be investigated. The influence of induced shear pressure, contact, and texture on the generated tactile details under different grasping modes will also be analysed to control robotic hand gripping input.

In this study [104], myoelectric prosthetic hands' lack of temperature perception restricts amputees' regular activities. Apart from five (5) amputee people, 22 healthy volunteers took part. According to the Linter approach, the study had a 31-day runtime and four test stages. A non-invasive temperature feeling approach is proposed for use in future studies to instruct amputees to sense temperature via psychophysical sensory replacement. With only one attempt at experimenting with the color temperature, the well-trained amputee participant successfully used the prosthesis to determine an object's temperature with a score of 72.58%.

In this study [105], The grip strength of a prosthetic hand usually results in a single vibration or electrical stimulation for people with upper extremity disabilities when they hold an object. In this study, we use the CNN-LSTM model, sensory voting, and the probability mass function techniques to analyse and predict how many interesting factors influence people's perceptions. Multiple human sensory responses were expected using a CNN-LSTM model built and trained on data from prosthetic hand grips, item temperatures, and the hardness of objects clutched by the prosthetic hand. The trained neural network model's predicted probability quality function agrees reasonably well with the acquired sensory voting distribution of percentages.

This research [106], Describes a robotic hand tactile sensing system with multiple digits capable of detecting dispersed contact forces and tactile data during dexterous multimodal grasping applications. The robotic hand's thumb, index, and middle numbers are equipped with various touch sensors. Six distinct grasping modes are chosen for dexterous robotic grasping, and object-grasping evaluations are conducted. By examining the automated hand grasp actions in each grasping manner, the characteristics of the detected tactile forces can be studied and contrasted, and this analysis can be used to differentiate the grasping modes further.

Table 1: Summary of research papers on bionic hand published in different journals and conference paper

Years	IEEE	Springer	Research gate	Elsevier	Other Journal	Conferences	Total
2006	__	[107]	__	__	__	__	1
2007	__	__	__	__	[108]	__	1
2008	[109]	__	__	__	__	__	1
2009	[110]	__	[111]	__	__	__	2

Years	IEEE	Springer	Research gate	Elsevier	Other Journal	Conferences	Total
2010	[112]	__	__	__	__	[113]	2
2011	[114]	__	[115]	__	__	[116]	3
2012	[117]	__	__	[118]	[119]	[120, 121]	5
2013	__	[122]	__	__	[123-125]		4
2014	__	[126, 127]	__	__	[128, 129]	[130-132]	7
2015	[133]	[134]	__	[135]	__	[136]	4
2016	__	__	__	__	__	[137, 138]	2
2017	__	__	__	__	[139]	[140]	2
2018	__	[141]	__	__	[142, 143]	__	3
2019	[144, 145]	__	__	__	[146, 147]	__	4
2020	__	__	__	[148]	__	__	1
2021	__	[104, 149]	[150]	__	[151, 152]	__	5
2022	__	__	__	__	[95, 153, 154]	__	3
2023	__	__	__	__	[1]	_	1

3. Prosthetic hand

3.1. Categories based on sensors

3.1.1. Pressure sensor

As sensor technology has developed, it has been increasingly used in robotic hand applications. Among these sensors is the piezoresistive one. The Flexiforce sensor uses a resistive system in which the resistance decreases as the applied force increases. These sensors produce millivolt-range signals. Therefore signal amplification is required. Piezoelectric resistance. The present investigation has employed the Flexiforce sensor with a range of 0-25 lb/(llON), as depicted in Table 2, and has also reviewed pertinent scholarly works. Piezo resistive technology offers several advantages that can enhance the precision and dependability of pressure distribution measurements. These benefits include affordability, sensitivity to sound, straightforward design, extended stability with minimal noise, and linear response to applied pressure [132]. A flexible capacitive sensor for measuring plantar pressure has been developed in biomechanical applications. The sensor had four layers: a lower layer, a dielectric layer, an upper layer, and a bump layer. The variation in capacitance values can effectively represent the applied pressure[118]. Integrating a ferroelectric polymer

sensing layer into a flexible pressure sensor has been implemented to measure dynamic pressure during robotic grasping. The sensing layer processed through a solution features a ferroelectric polymer with a higher molecular weight and a processing solvent. The proposed sensor exhibits rapid response and high-pressure sensitivity [153].

Table 2: Summary of research papers on bionic hand using pressure sensor

Sensor type	Reference	Venue	Hardware used	Year	total
Pressure	[118]	Journal	Microelectronic Engineering	2012	233
Pressure	[123]	Conference	The RSM 2013 IEEE Regional Symposium on Micro and Nanoelectronics	2013	18
Proximity ,Pressure	[126]	Journal	Nano Research	2014	114
Pressure	[127]	Journal	Microsystem technologies	2014	65
Pressure Sensor	[132]	Conference	IEEE International Symposium on Robotics and Manufacturing Automation.	2014	8
Pressure ,Proximity, Grapping	[95]	Journal	ACS Applied Electronic Materials	2022	5
Pressure Sensor	[153]	Journal	Advanced Functional Materials	2022	

3.1.2. Temperature sensor

Psychophysical sensory substitution is proposed to train amputees to perceive temperature. This research involved 22 healthy participants and five amputees. The investigation lasted 31 days and consisted of four Leitner technique test steps. The temperature of the water/phantom digits was changed using a temperature-adjustable cup and a Peltier to elicit temperature in the subjects. Table 3 is a summary of a research article. To further separate the user from their surroundings and showcase colour, a VR glass was also utilised. The questionnaire responses were used to compile the statistical findings. The results of the chi-square tests indicated that the Leitner technique was successfully implemented by the participants (P = 0.05). The "Repeated Measures ANOVA" also found a statistically significant (P 0.001) difference in the length of time people were numb. In addition, the well-trained amputee respondent using the prosthesis correctly identified the object's temperature 72.58% of the time after only one experiment with the colour temperature. Participants remembered the lowest and highest temperatures significantly better than others (P = 0.001) [104].

Table 3: Summary of research papers on bionic hand using pressure sensor

Temperature	[104]	Journal	Springer	2021	1
Temperature	[104]	Journal	Journal of Bionic Engineering	2021	3

3.1.3. Grip force

Robotic hands can generate grip force through the use of actuators, which are devices that convert electrical or hydraulic power into mechanical force. The type and number of actuators used will depend on the design of the

robotic hand, as well as the desired grip strength and dexterity.One common type of actuator used in robotic hands is the electric motor. Capacitive sensors and a literature study (Table 4) that can halt an approaching process and trace a step force are consumed for gripping control on the artificial hand [95].Electric motors can be controlled with great precision and can generate high forces, making them well-suited for applications that require strong grip forces. Other types of actuators that can be used in robotic hands include hydraulic cylinders, pneumatic cylinders, and shape memory alloys.The grip force generated by a robotic hand will depend on a variety of factors, including the type and number of actuators used, the design of the hand, and the intended application.

Table 4: Summary of research papers on bionic hand using pressure sensor

Prosthetic Hand	[107]	Journal	Biological cybernetics	2006	396
Perception	[108]	Journal	Proceedings of the National Academy of Sciences	2007	550
Robotic Hand	[109]	Journal	EEE/RSJ International Conference on Intelligent Robots and Systems	2008	22
Prosthetic Hand	[110]	Journal	IEEE/ASME transactions on mechatronics	2009	261
Prosthetic Hand	[111]	Journal	Am. J. Biomed. Sci	2009	40
Bionic hand dynamic interaction	[113]	Conference	IEEE	2010	16
Prosthetic Hand	[115]	Journal	perspective	2011	
Precise Motion	[116]	Conference	IEEE	2011	1
Vibrotactile Sensory Modality	[114]	Journal	IEEE Transactions on Robotics	2011	166
Prosthetic Hand	[120]	Conference	IEEE	2012	2
Human Hand	[121]	Conference	41st International Conference on Environmental Systems	2012	22
Soft Robot Arm	[119]	Journal	Advanced robotics	2012	881
Grip Force	[117]	Journal	IEEE Transactions on Neural Systems and Rehabilitation Engineering	2012	135
Grip Force	[124]	Conference	2013 IEEE/RSJ International Conference on Intelligent Robots and Systems	2013	60
Grip Force	[122]	Book section	Springer	2013	10
Prosthetic Hand	[125]	Conference	IEEE International Conference on Robotics and Automation	2013	268

Grip Force	[130]	Conference	IEEE/RSJ International Conference on Intelligent Robots and Systems	2014	116
Grip Force	[131]	Conference	IEEE	2014	18
Haptic Feedback	[128]	Journal	American Journal of Aerospace Engineering	2014	10
Pressure Sensor	[132]	Conference	IEEE International Symposium on Robotics and Manufacturing Automation (ROMA)	2014	8
Tactile Sensing	[129]	Journal	CoRR	2014	10
Grip Force	[136]	Conference	IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)	2015	41
Skin Mechanoreceptors	[134]	Journal	Pflügers Archiv-European Journal of Physiology	2015	40
Soft Robot Glove	[135]	Journal	Robotics and Autonomous Systems	2015	1246
Finger	[133]	Journal	IEEE Transactions on Systems, Man, and Cybernetics: Systems	2015	46
Soft Pneumatic Finger	[137]	Conference	IEEE International Conference on Rehabilitation Robotics (ICORR)	2016	41
Grip Force	[138]	Conference	IEEE	2016	40
Prosthetic Hand	[139]	Journal	Journal of Neurosurgery	2017	29
Grip Force	[140]	Conference	International Conference on Social Robotics	2017	13
Prosthetic Hand	[142]	Journal	Science Robotics	2018	139
Prosthetic Hand	[143]	Journal	Science robotics	2018	216
Grip Force	[141]	Journal	Acta Mechanica Solida Sinica	2018	22
Sensory Feedback	[146]	Journal	Science Robotics	2019	174
Prosthetic Hand	[144]	Journal	Ieee Access	2019	66
Grip Force	[147]	Journal	Nature	2019	460
Grip Force	[145]	Journal	IEEE Transactions on Electron Devices	2019	16

Joint torque	[148]	Journal	Measurement	2020	8
Grip Force	[151]	Journal	Machines	2021	8
Prosthetic Hand	[150]	Journal	Research	2021	8
Skin	[152]	Journal	Journal of Clinical Medicine	2021	4
Prosthetic Hand	[149]	Journal	Science China Technological Sciences	2021	5
Grip Force	[154]	Journal	Journal of Mechanisms and Robotics	2022	

3.1.4. Proximity sensor

Integrating a ferroelectric polymer sensing layer into a flexible pressure sensor has been implemented to measure dynamic pressure during robotic grasping. The sensing layer processed through a solution features a ferroelectric polymer with a higher molecular weight and a processing solvent. The proposed sensor exhibits rapid response and high-pressure sensitivity[95].

Table 5: Summary of research papers on bionic hand using pressure sensor

Proximity	[99]	Conference	Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC	2021	2
Proximity	[99]	Conference	Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC	2021	2
Proximity ,Pressure	[126]	Journal	Nano Research	2014	114
Pressure ,Proximity, Grapping	[95]	Journal	ACS Applied Electronic Materials	2022	5

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3.2. Categories based on methods

3.2.1. CNN-LSTM neural network model

Using the data we've gathered, we can create and train a model to determine which factors significantly correlate with the probability of sensory voting for several people. First, we cannot use the sensory votes collected from individuals grasping objects as input for neural networks because we cannot obtain specific hardness and grip strength data from these sensory votes. A prosthetic hand with 11 pressure sensors was used to collect these data. We can now get grasp force data because the object's mass has changed, thereby altering the data collected by the sensor array. The independent variables that influence the output of a neural network should be represented by input neurons employing the methods detailed in Table 6. Figure 8 Shows the

structure of the neural network that was employed for this study. Object temperature, object hardness, and prosthetic hand gripping force are the three grasping elements of the input layer. We want to calculate the likelihood of a seven-neuron vote in the output layer for each neural network model.

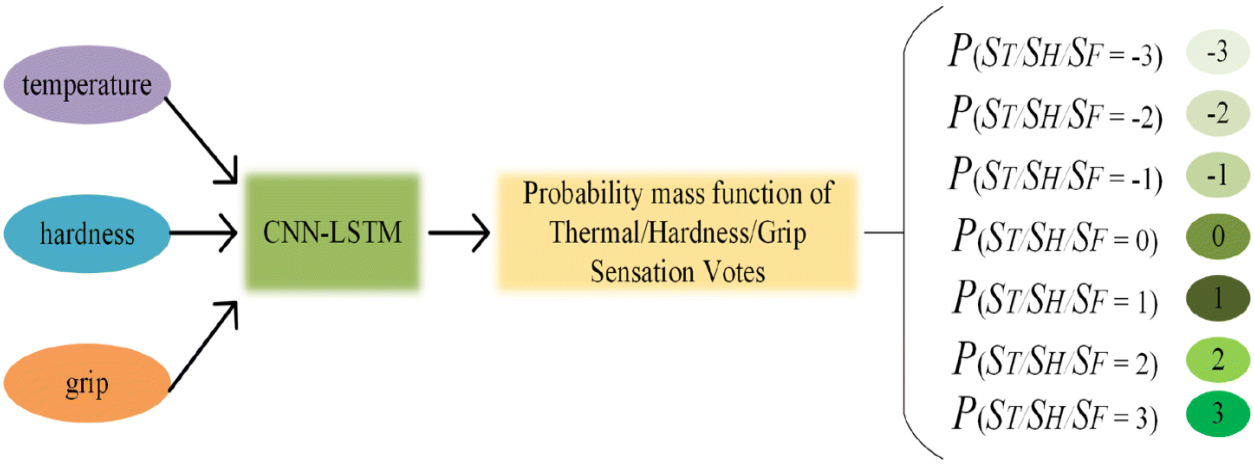


Figure 8: The overall structure of the CNN-LSTM taken from [105]

3.2.2. Artificial neural network (ANN)

The data acquired can be used to build and train a model that correlates different variables with people's odds of voting using their senses. An example of a neural network (Figure 9) that cannot take sensory inputs on an object's hardness and grip strength as input. We used a robotic hand with eleven pressure sensors to obtain these readings. The prosthetic hand handles it typically and slowly before lifting it. The change in the acquired data from the sensor array allows us to calculate the object's grab force.

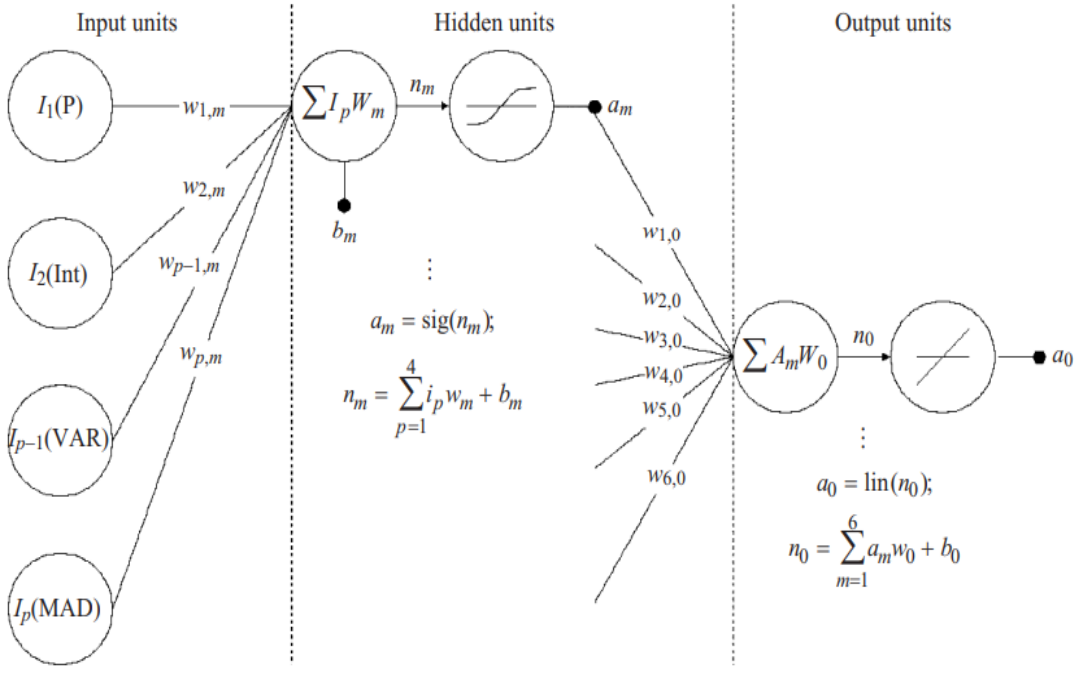


Figure 9: The overall structure of the neural network taken from [155]

Table 6: A summary of various bionic hand methodologies

References	Methodology/ toolkit	Equipment/ dataset	Evaluation Measure	Limitation
2022, [156]	Fast Fourier Transform (FFT) method, Multi-layer perceptron method(MLP)	EEG sensor, Raspberry Pi, AF7 electrode, TP9 electrode	Accuracy of movement = 77.20% With head movement was 84.40%	Accuracy
2022, [106]	The design of tactile sensors forms the basis of the tactile sensing system.	Scan circuit board, tactile sensor, EMG signal, Grasping modes, control modules	In the range of 2 N, the sensor's calibration result is 0.370 V/N, while in the field of 28 N, it is 0.019 V/N.	The feature characteristics of tactile forces under various grasping modes are excluded from the analysis.
2022,[95]	Finite element analysis (FEA)	Capacitive sensor, electrode, pressure sensor	Fingers can move within 100° of each other.	Surface area on the finger, the sensing unit's diameter is limited to 3 mm.
2022, [102]	Data processing, linear discriminant analysis algorithm (LDA)	Driving finger motor, drive thumb motor, tip of the finger, coil spring, the palm, connection rod, EMG sensor	Accuracy = 96.59%	The hand's function and availability, and make it more accessible to people
2022,[105]	CNN-LSTM model	Pressure sensor	The thermal sensation is nearly 96.2% accurate, while toughness and grasp strength are approximately 93.6% and 94.2% correct, respectively.	The number of datasets is a limitation.
2021, [99]	Signal Acquistion, Training Data, and Decoding Techniques for a Semi-Autonomous Prosthetic hand	EMG sensor, multi-modal fingertip sensors	Using their dominant hand, participants completed the two tasks in 2.7 0.3 s and 2.4 0.2 s, respectively, for the simple and challenging settings.	Although the machine control outperformed the human (semg) control, it was specifically designed to work with fragile objects, which is a study limitation.
2021, [100]	Artificial neural network (ANN)	Pressure sensor, tactile sensor, temperature sensor	Accuracy 92.7% and 95.9%	The movement of hand is difficult.

References	Methodology/ toolkit	Equipment/ dataset	Evaluation Measure	Limitation
2021,[157]	Designed in SOLIDWORKS and printed on a 3D printer	EMG ,3D Printer	Grasp objects according to the user's desire	Accuracy
2021,[101]	Acrylamide, diacrylate, 1-Hydroxycyclohexyl phenyl keton, calcium chloride hexahydrate	Tactile sensor, processing unit, pressure sensor	When the compressive ability of the PC-gel changed, the pressure sensor's sensitivity went from low to high.	The results of this study offer a novel and promising approach to developing soft robotics and electronic skin with programmable but not temperature-dependent properties..
2021, [158]	Neural-network method	Arduino microcontroller, Arduino	There are three groups of items, including both models and real-world samples, ranging in size, form, and rigidity.	Proximity, temperature
2020,[96]	Semg control	Temperature and pressure sensors	Acuuracy = ±1◦C	Proximity
2020,[159]	SOFA framework	One Arduino board, one chamber, and zero to fifty kilopascals	Our soft hand demonstrates postural dexterity by being capable of 32 of the 33 grasp postures described by the Feix taxonomy.	Thumb abduction and finger-splaying angles are constrained by the air chamber's structure, which is made of silicone and has a high tensile strength and thick walls.
2020,[159]	Deep Neural Network (DNN, Gaussian Mixture Model (GMM)	Tactile sensor, biotac sensor	The slip classifier has a high accuracy of about 98% and a detection accuracy of about 95% in terms of material detection.	To obtain ground truth force data, force calibration of the Biotac sensor based on a force/torque sensor is performed.
2019,[160]	Neural Network classifier	Pressure Sensor , Temperature senor , Fabrication of Porous Functional Material Doping with Silver Nanoparticles:	Dynamic gripping with a 95% accuracy in object recognition	Proximity
2019,[	Imus and optical	Haptic Glove,	Users identified	The robotic hand's opposability

References	Methodology/ toolkit	Equipment/ dataset	Evaluation Measure	Limitation
161]	curvature sensors	Curvature Sensors Haptic Muscles	poor grasps with 60% accuracy and good grasps with 86% accuracy.	and other capabilities
2019, [97]	Convolutional neural network	Biotac SP Images dataset, Tactile sensors	92.7% accuracy	The project's limitation is defining graph connectivity.
2019, [162]	Sensory panel measurement, scan network	Tactile sensor array	Fitting accuracies OF axes z- = 3.93% x-=10.52% y- 11.81%	The optimal threshold settings for the wavelet coefficients of the tactile sensor array to detect slippage have yet to be investigated.
2018, [163]	Micro-laser Doppler velocimeter (μ-LDV)	Velocity sensor, stepping motor, laser displacement sensor	The results show that the -LDV can detect slip and measure slip velocity in real time at a high response speed of 50 ms.	Due to its large size, the use of a laser Doppler velocimeter as a slip sensor for a robotic hand fingertip has been limited.
2017,[164]	On a polydimethylsiloxane (PDMS) base, a 1.0 m thick copper (Cu) layer is sandwiched between a 20 nm dense chromium (Cr) layer and a 5 m thick polyimide (PI) layer.	Capacitive sensor with stretchable polydimethylsiloxane (PDMS) substrate and a parallel plate structure (PPS)	Accuracy = 90%	Limited results
2017,[165]	Slipping and sticking effects from both the non-linear normal force and the non-linear tangential friction force	A artificial hand equipped with tactile sensors, an elastic ball, and a foam cubes with several fingers.	When grasp stability is reached, the simulation is terminated, and the final contact forces are returned as a result.	The fingers will not only restrain the deformable object, but will also move and reorient it within the robotic hand.
2016,[166]	The pleated shape of a fluidic elastomer robot inspires the idea of a soft finger design.	An Objet260 Connex-printed, three-fingered soft gripper.	During the successful lift, three curvature sensors were used.	A mathematical model will examine the soft finger's curvature and motion.
2016,[167]	Supervised and Unsupervised learning	Raspberry Pi 2 and Arduino UNO, Sensors	Good grasping capabilities of the device.	The system cannot be used on other prostheses with different attributes, such as temperature

References	Methodology/ toolkit	Equipment/ dataset	Evaluation Measure	Limitation
	approaches	,Camera Pressure Sensor		and pressure, such as lower limb and craniofacial prostheses.

4. Current challenges

The configuration and behaviour of the robotic hand presented the most significant challenge when carrying out pick-and-place operations. There are currently difficulties with opposability and other qualities that must be overcome by the robotic hand.

1. Material availability is a major issue.
2. Expensive material for prosthetic hand
3. In order to achieve advanced control, which is not currently possible, a secure connection between man and machine is necessary.
4. A crucial future perspective is patient care in specialized facilities for bionic reconstruction. These centers will enhance research as well as treatment protocols and clinical outcomes because they ideally bring together specialists in basic and clinical research with skilled surgeons and top-notch rehab infrastructure.
5. Given the range of control possibilities, including threshold-based control, co-contraction, pattern recognition, and proportional and simultaneous control, patients would need extensive training before entirely using the new mechatronic hand. As a result, preparation for surgery and prosthetic fitting occurs throughout rehabilitation.
6. severely limited efficient sensors and control algorithms
7. Bionic hands require a source of power, which can be a challenge to provide in a compact and efficient manner. Battery life is also a critical factor, and improving battery technology to extend the lifespan of the hand between charges is an ongoing challenge.
8. Sensory feedback from proximity and tactile sensing can help amputees with spatial awareness and grasp by providing additional sensory information.

5. Conclusion

In this study, we review different pressure sensors, proximity sensors, temperature sensations, and precise grip force techniques. Similarly, various methods, such as neural network, Deep Neural Network (DNN), CNN-LSTM model, Finite element analysis (FEA), etc. are reviewed in this study. The prosthetic hand still struggles to look and perform like a natural hand due to compatibility issues and signal instability. Eighty publications were chosen for this purpose and evaluated based on the performance criteria; the search focused on articles published between 2006 and 2022. Overall, this analysis provides a firm groundwork for developing brighter bionic hands that may work with a user to improve agility and reduce mental strain. Recognising the qualities of objects based on their weight will be a primary focus of future research. This review assists to researchers, doctors, amputees, and artificial limb institutes.

Because of the author's extensive review in Bionic Hand, the following recommendations and considerations are made:

1. Defining a specific task for a prosthesis can be beneficial. A simple and robust prosthesis for daily life tasks is preferred.
2. Capacitive sensors provide a more stable grip in power grasp patterns.

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