IJAREEIE

e-ISSN: 2278-8875
p-ISSN: 2320-3765

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

Volume 10, Issue 8, August 2021

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 7.282

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering (IJAREEIE)

| e-ISSN: 2278 – 8875, p-ISSN: 2320 – 3765| www.ijareeie.com | Impact Factor: 7.282| || A Monthly Peer Reviewed & Referred Journal |

|| Volume 10, Issue 8, August 2021 ||

| DOI:10.15662/IJAREEIE.2021.1008050 |

The Evolution of Artificial Intelligence in Healthcare: Historical Insights, Current Applications, and Future Prospects

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ABSTRACT: The goal of artificial intelligence (AI) is to simulate human cognitive processes. Thanks to the quick development of analytics techniques and the expanding availability of healthcare data, it is revolutionising the field of healthcare. We examine the state of AI applications in healthcare now and talk about their prospects. AI is applicable to both organised and unstructured healthcare data. Popular artificial intelligence (AI) approaches include natural language processing for unstructured data and machine learning techniques for structured data, such as the traditional support vector machine and neural network and the more recent deep learning. Three major illness areas that use AI techniques are neurology, cardiology, and cancer.

KEYWORDS: Artificial Intelligence in Healthcare, Historical Development, Current Applications, Future Prospects, Healthcare Innovation

I. MEDICINAL ARTIFICIAL INTELLIGENCE (AI) RESEARCH OVERVIEW

In recent times, advancements in artificial intelligence have significantly impacted the healthcare sector, sparking a lively debate regarding the potential for AI to supplant human doctors in the future. It is our position that while machines are unlikely to fully replace human physicians in the near term, AI can certainly enhance the decision-making capabilities of healthcare professionals and may even take over certain aspects of clinical judgment, particularly in specialized fields such as radiology. The growing accessibility of healthcare data, coupled with the swift evolution of big data analytics, has facilitated the successful integration of AI technologies within the healthcare landscape. Informed by pertinent clinical inquiries, advanced artificial intelligence methodologies have the potential to reveal clinically significant insights concealed within vast datasets, thereby facilitating improved clinical decision-making. This article provides an overview of the present landscape of AI in the healthcare sector while also contemplating its future trajectory. Initially, we will succinctly examine four key dimensions from the viewpoint of medical researchers:

The reasons behind using AI in healthcare.
1. Data kinds that AI has examined systems.
2. The methods that allow AI to produce clinically significant outcomes
3. The diseases that the AI communities are presently attempting to treat

II. MOTIVATION

The medical literature has covered AI's benefits in great detail. Artificial intelligence (AI) may leverage complex algorithms to "learn" features from a vast amount of medical data, and then apply the knowledge gained to improve clinical practice. Additionally, it can be given the capacity to learn and self-correct in order to increase accuracy in response to criticism. In order to support appropriate patient care, an AI system can help doctors by supplying current medical information from journals, textbooks, and clinical practices. Six Furthermore, an AI system can aid in lowering therapeutic and diagnostic errors which are unavoidable in human clinical practice. Additionally, an AI system gathers relevant data from a sizable patient base to help with inferences for health outcome and danger alert in real time.

III. MEDICAL INFORMATION

AI systems must be "trained" using data generated from clinical activities, such as screening, diagnosis, treatment assignment, and so forth, before they can be used in health-care applications. This is done to enable the systems to identify subjects that are similar to one another and to establish links between the characteristics of the subjects and

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outcomes of interest. Clinical data can take various forms, such as demographics, electronic records from medical equipment, physician notes, physical examinations, clinical laboratory imaging, and more. To be more precise, a significant amount of the AI literature examines data from electro diagnosis, genetic testing, and diagnostic imaging during the diagnosis stage. For example, when assessing diagnostic images that contain a large amount of data, radiologists should use AI technology. Li and colleagues investigated the application of aberrant genetic expression in long non-coding RNAs for the diagnosis of gastric cancer. Shin et al. created a system to facilitate electro diagnosis in order to localise brain damage

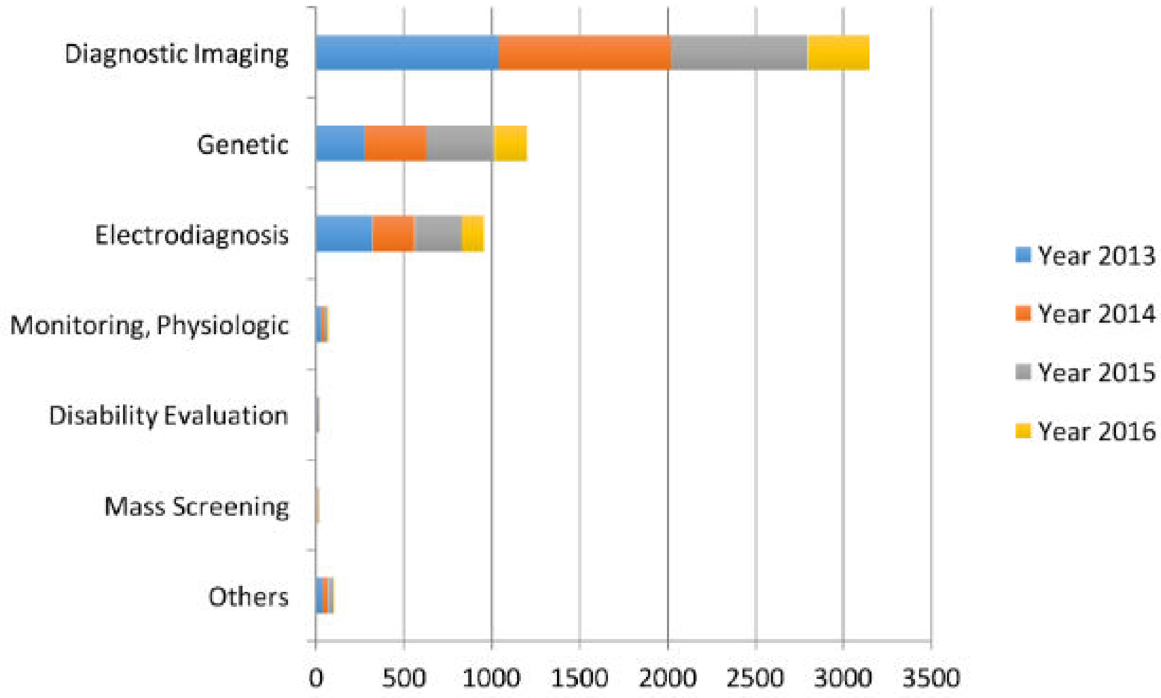

Figure 1. Medical Information

Furthermore, physical examination documentation and clinical laboratory findings represent two additional primary sources of data, as illustrated in figure 1. We differentiate these sources from image, genetic, and electrophysiological (EP) data due to their substantial amounts of unstructured narrative content, including clinical notes, which are not readily amenable to analysis. Consequently, the relevant AI applications prioritize the transformation of this unstructured text into a format that can be interpreted by electronic medical records (EMR). For instance, Karakulah. employed AI technologies to extract phenotypic characteristics from case reports, thereby improving the diagnostic accuracy of congenital anomalies.

IV. AI GADGETS

According to the explanation above, there are two basic categories into which AI devices can be divided. Machine learning (ML) approaches that analyse structured data, such as genetic, imaging, and EP data, fall under the first category. In medical applications, machine learning algorithms try to group characteristics of patients together or estimate the likelihood of a disease's course. Natural language processing (NLP) techniques fall under the second group. These techniques take information out of unstructured data, including clinical notes and medical journals, and use it to enhance and augment structured medical data. The goal of NLP methods is to convert texts into structured data that can be read by machines so that machine learning algorithms may examine it. The flow chart illustrates the path from clinical data collection to clinical decision making, including NLP data enrichment and ML data analysis, for improved presentation. We observe that clinical actions are where the route map begins and concludes. Even if AI techniques have great potential, they must ultimately be utilised to support clinical practice and driven by clinical challenges.

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V. ILLNESS-FOCUSED

- **Cancer:** Through a double-blinded validation research, Somashekhar et al. Showed that the IBM Watson for oncology would be a trustworthy AI system for aiding in the detection of cancer. 19 To determine the subgroups of skin cancer, Esteva et al. examined clinical pictures.
- **Neurology:** Bouton et al. Created an AI system to help quadriplegic patients regain control over their movements. Farina et al. evaluated the efficacy of an off-line man-machine interface that controls upper-limb prosthetics by means of spinal motor neurone discharge timings.
- **Cardiology:** Dilsizian and Siegel talked on how an AI system might be used to diagnose heart illness using cardiac imaging. The US Food and Drug Administration (FDA) has given Arterys permission to sell its Arterys Cardio.

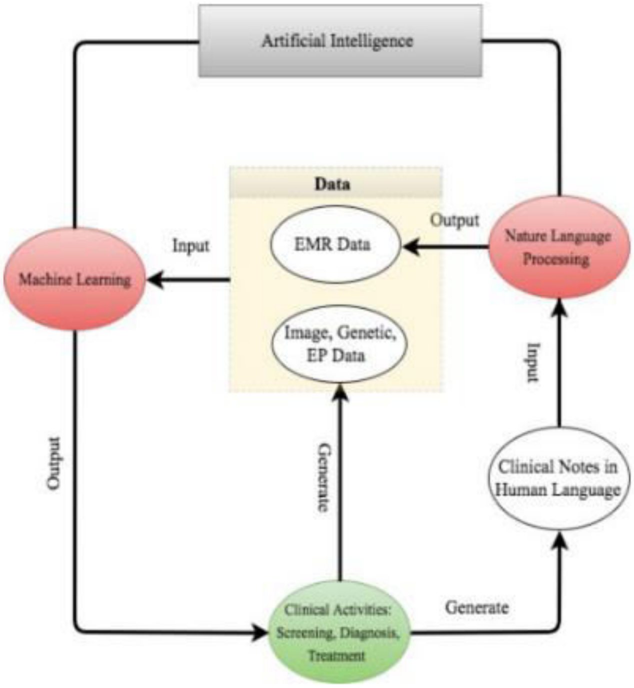

Figure 2. Artificial Intelligence in Medicine

It is not entirely surprising that there is a concentration around these three illnesses. Since these three illnesses are the main causes of death, it is imperative to diagnose patients at an early age to stop their health from getting worse. Additionally, one of the AI system's strengths is its ability to potentially obtain early diagnoses through enhancing the analytic procedures on imaging, genetic, EP, or EMR. AI has been used to treat illnesses other than the three main ones. Two recent instances are Long et al. (diagnosed congenital cataract disease by analysing ocular image data) and Gulshan et al. (identified referable diabetic retinopathy by analysing retinal fundus pictures).

VI. AI GADGETS: ML AND NLP

We go over the AI tools (or methods) that have proven helpful in the medial applications in this part. The classical machine learning approaches, the more modern deep learning techniques, and the NLP methods are the three divisions into which we divide them.

6.1 Traditional ML

Machine learning creates data-analytical algorithms to extract features. "Traits" of the patient as well as occasionally interesting medical results are inputs used by ML systems. The characteristics of a patient often consist of baseline information like age, gender, past medical history, and so on, as well as information specific to the disease such findings from a physical examination, EP tests, diagnostic imaging, gene expressions, clinical symptoms, medication, and so forth. In addition to the characteristics, clinical research frequently gathers patient medical outcomes. These

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include of illness markers, patient survival rates, and numerical disease levels, like tumour diameters. In order to make corrections, we identify the jth characteristic of the ith patient by Xij and the desired result by yi.

Unsupervised learning and supervised learning are the two main categories into which machine learning algorithms fall, depending on whether or not the results are taken into account. While supervised learning is useful for predictive modelling by establishing some links between the patient traits (as input) and the desired outcome (as output), unsupervised learning is well known for feature extraction. Semi supervised learning is a hybrid approach that combines supervised and unsupervised learning techniques. It is useful in situations where specific topics do not achieve the desired conclusion. This approach has gained popularity recently. Figure 4 depicts these three categories of learning.

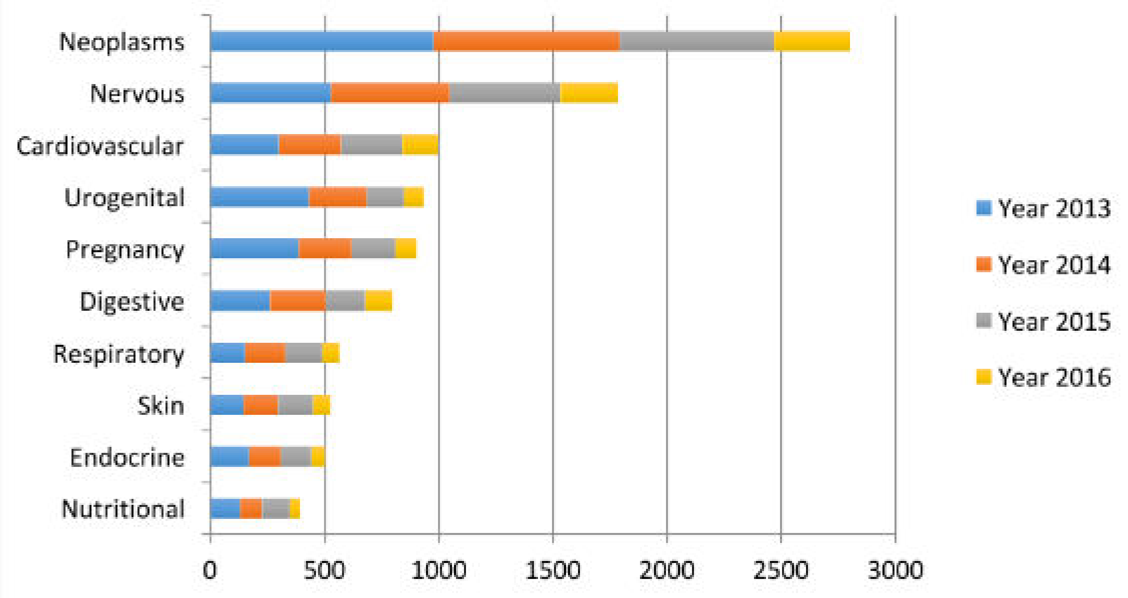
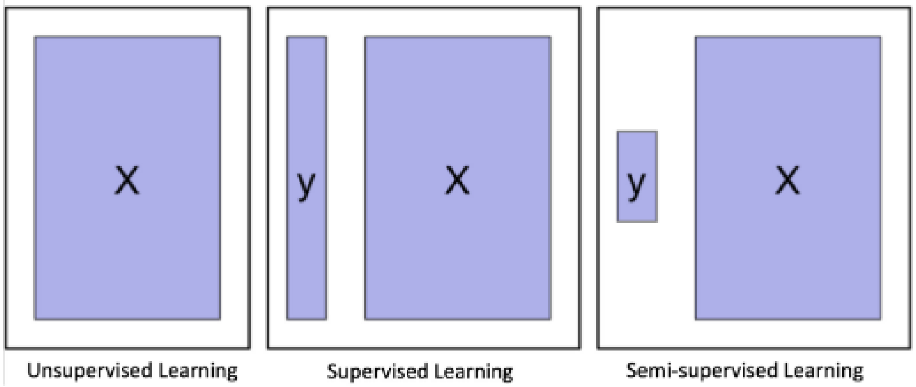


Figure 3. History of AI in Medicine

Principal Component Analysis (PCA) and clustering are two popular unsupervised learning techniques. By clustering, people with comparable features are grouped together without reference to the outcome data. Through maximising and minimising the similarity of the patients both within and between groups, clustering algorithms produce the cluster labels for the patients. K-means clustering, hierarchical clustering, and Gaussian mixture clustering are a few common clustering algorithms. PCA is primarily used for dimension reduction, particularly in cases when a trait is measured across numerous dimensions, as in the case of a genome-wide association research with many genes. PCA projects the data in a few principle component (PC) directions while preserving a significant amount of subject-specific information. Sometimes it is possible to group the individuals using clustering after using PCA to initially reduce the dimension of the data.



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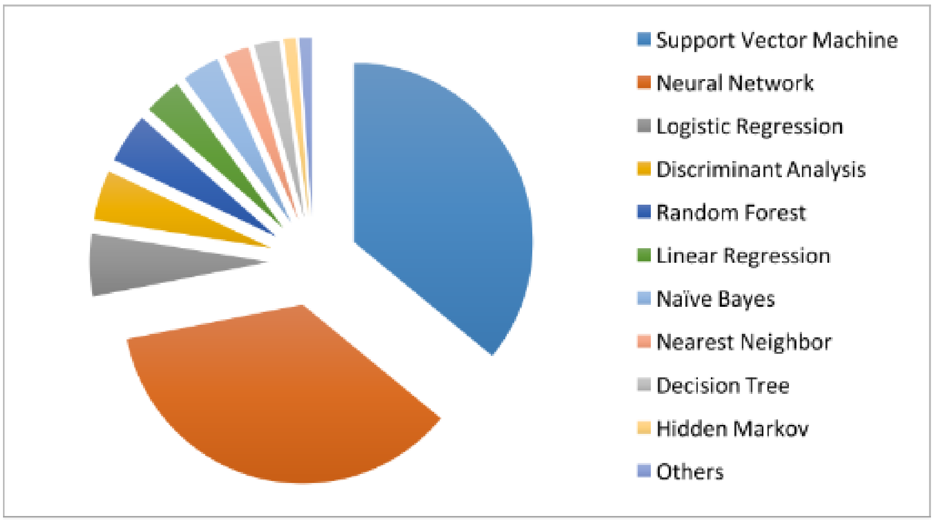


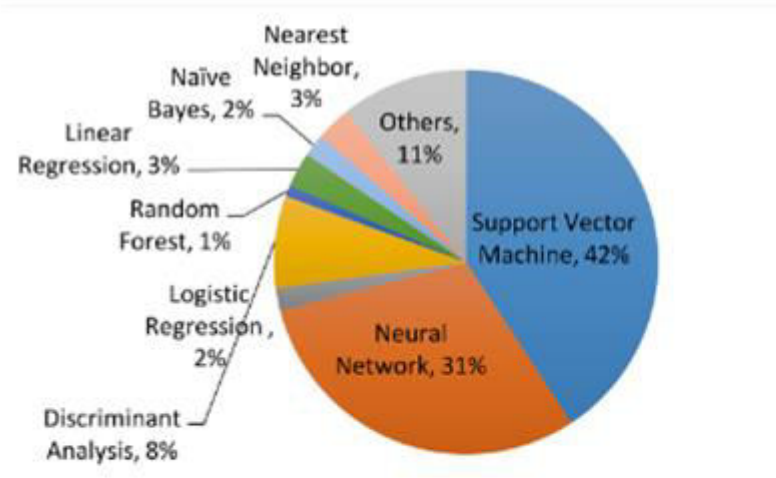
Figure 4. ML Algorithms in Medical Literature

6.2 Support Vector Machine

SVM is generally used to divide the subjects into two groups, with Y i serving as a classifier and representing whether the ith patient is in group 1 or 2, accordingly, with Y i = −1 or 1. If there are more than two groups in a situation, the procedure can be expanded. The fundamental premise is that the subjects can be divided into two groups by means of a decision boundary based on the attributes Xij, which can be expressed as follows:

Let ai = ∑p}j = 1 w j X ij + b.

Finding the ideal w js will allow the final classifications to agree with the outcomes as much as possible; in other words, the training goal is to discover the minimum misclassification error—that is, the error of classifying a patient into the incorrect group. It seems sense that the optimal weights should permit: (1) an i's sign to match Y i's so that the classification is accurate; and (2) an i's distance from 0 so that the classification's ambiguity is minimised. These can be attained by making choices that minimise a loss function that is quadratic. 29 Additionally, the generated can be used to categorise the new patients according to their characteristics, presuming that they are from the same community.



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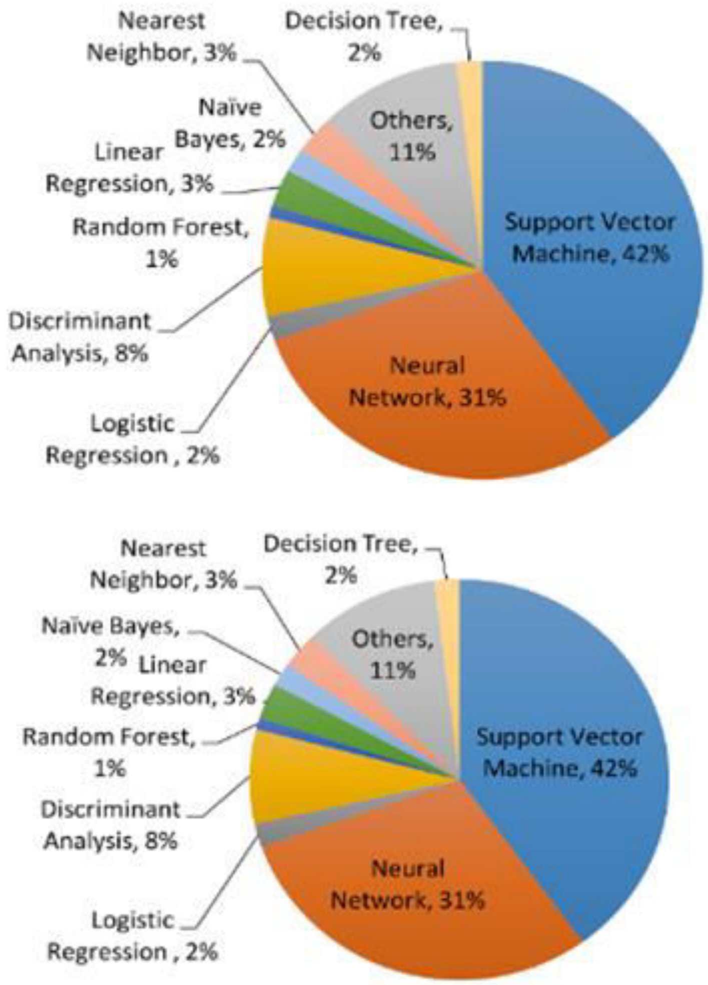

Figure 5 Represents Analysis of Medical Data

6.3 Deep learning: a new era of ml

A contemporary development of the traditional neural network method is deep learning. You can think of deep learning as a multi-layered neural network.

The swift advancement of contemporary computing allows deep learning to construct neural networks with numerous layers, an impracticality for classical neural networks.

Deep learning can therefore examine more intricate non-linear patterns in the data. The rise in volume and complexity of data is another factor contributing to deep learning's recent prominence. In 2016, the use of deep learning in the field of medicine almost doubled. Furthermore, demonstrates that a resounding majority of deep learning is applied to picture analysis, which makes sense considering the enormous volume and inherent complexity of images. Deep learning has more hidden layers than a traditional neural network, enabling algorithms to handle complex data with a variety of architectures.27 Deep learning methods such as convolution neural network (CNN), recurrent neural network, deep belief network, and deep neural network are frequently employed in medical applications. Their patterns and relative popularity are shown in Figure 12 for the years 2013 through 2016. It is evident that the CNN is the most well-liked network in 2016.

The current landscape of deep learning is illustrated in Figure 10, which presents data derived from searches related to deep learning within the healthcare and disease categories on PubMed. The input values are processed through a training mechanism that adjusts the weights to minimize the average discrepancy between actual outcomes and

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predicted results. Convolutional Neural Networks (CNNs) have been integrated into widely used software frameworks, including Caffe from Berkeley AI Research, CNTK from Microsoft, and TensorFlow from Google. Recently, CNNs have shown promising results in the medical field, particularly in aiding disease diagnosis. For instance, Long et al. utilized CNNs to diagnose congenital cataracts by analyzing ocular images, achieving an accuracy exceeding 90% in both diagnosis and treatment recommendations. Similarly, Esteva et al. employed CNNs to detect skin cancer from clinical images, with both sensitivity and specificity rates surpassing 90%, highlighting the method's exceptional performance. Furthermore, Gulshan et al. implemented CNNs to identify referable diabetic retinopathy using retinal fundus photographs, also reporting sensitivity and specificity rates above 90%, thereby underscoring the technique's efficacy in diabetes diagnosis. It is important to note that the performance of CNNs in these applications is consistently high.

VII. CONCLUSION

We examined the rationale behind the integration of artificial intelligence in the healthcare sector, highlighting the diverse types of healthcare data that AI has been utilized to analyze, as well as the primary disease categories where AI applications have been implemented. Subsequently, we provided an in-depth discussion of the two principal categories of AI technologies: machine learning (ML) and natural language processing (NLP). In our exploration of ML, we concentrated on the two most widely recognized classical methodologies: support vector machines (SVM) and neural networks, in addition to the contemporary approach of deep learning. Furthermore, we reviewed the three predominant categories of AI applications specifically related to stroke care. 2. An effective AI system must incorporate the machine learning component to manage structured data, such as images, electronic patient data, and genetic information, alongside the natural language processing component for extracting insights from unstructured text. These advanced algorithms require extensive training on healthcare data to enable the system to provide valuable assistance to healthcare professionals in diagnosing diseases and recommending treatment options.

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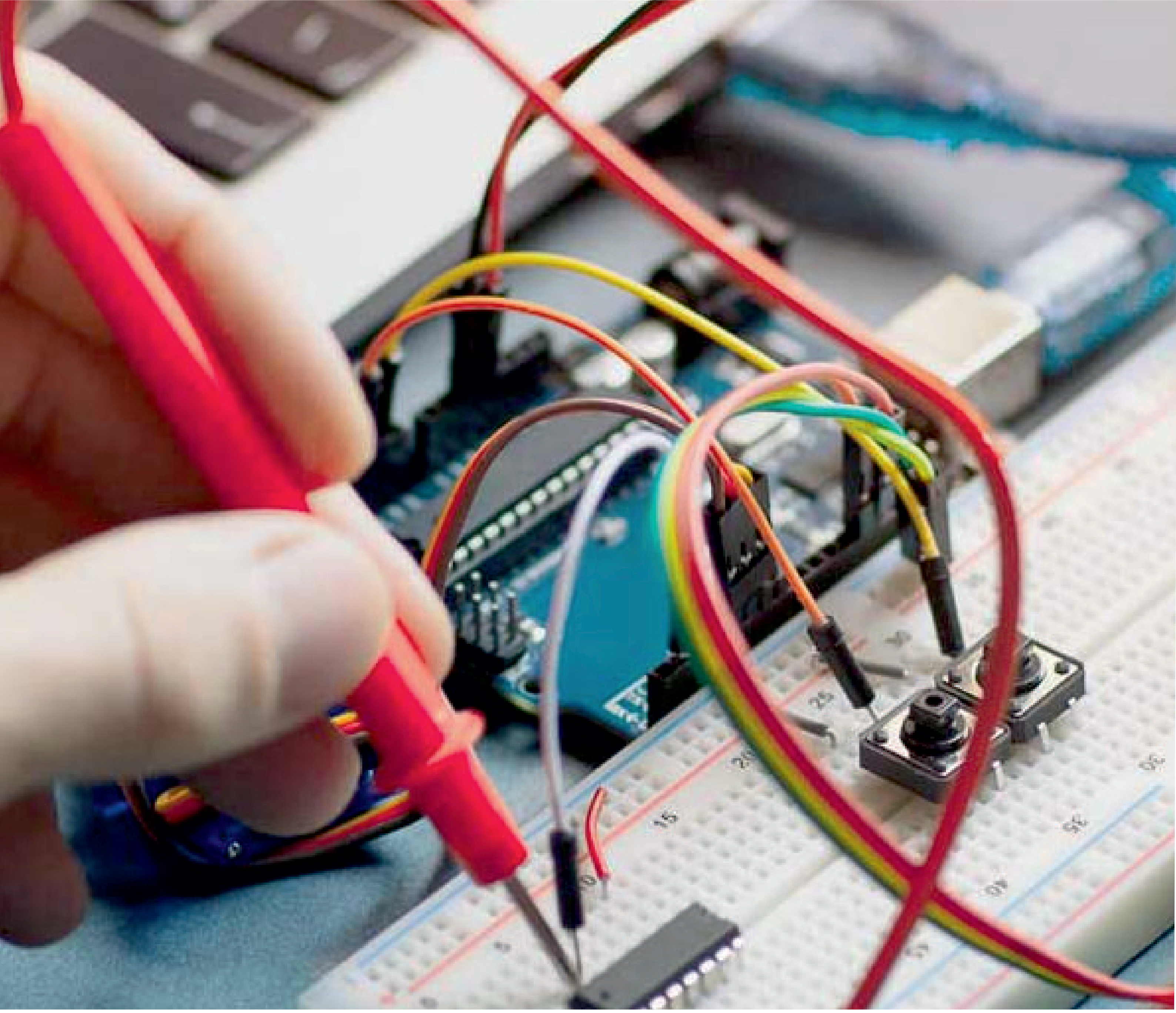

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