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Smart Health Card Using Neural Network

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Abstract: *Monitoring systems in hospitals and other health organizations have exploded in popularity over the last decade, and wireless healthcare monitoring devices using various technologies have attracted interest in many countries across the world. People are capable of to a variety of diseases as a result of their living habits and the state of the environment. As a result, predicting sickness at an early stage becomes a critical task. However, doctors find it challenging to make precise predictions based on symptoms. The most difficult challenge is correctly predicting sickness. To solve this problem, data mining plays a critical role in disease prediction. Medical science generates a vast amount of data each year. The proper analysis of medical data has been benefited from early patient care due to the increased amount of data growth in the medical and healthcare fields. Data mining uses disease data to uncover hidden pattern information in massive amounts of medical data. We developed a broad disease prediction based on the patient's symptoms. We use CNN algorithm to predict the disease.*

Keywords: Health Card, CNN (Convolutional Neural Network), Classification.

I. Introduction

Artificial intelligence has made computers smarter and has given them the ability to reason. Machine learning is considered a subfield of AI research in a number of studies. Different experts believe that insight cannot be gained without learning. Unsupervised, Semi-Supervised, Supervised, Reinforcement, Evolutionary Learning, and Deep Learning are examples of Machine Learning Techniques. These learning's are used to quickly classify large amounts of data. For quick classification of huge data and accurate disease prediction, we employ the K-Nearest Neighbor (KNN) and Convolutional neural network (CNN) machine learning algorithms. Because medical data is growing at an exponential rate, using it to predict the correct disease is becoming increasingly important. However, because processing big data is becoming increasingly important in general, data mining plays an increasingly important role, and classification of large datasets using machine learning is becoming increasingly simple. It's crucial to know how to make a correct diagnosis of a patient through clinical examination and evaluation. Decision assistance systems that rely on computers may become vital for making compelling decisions. The health-care industry generates a lot of data regarding clinical evaluations, patient reports, cures, follow-up appointments, medicine, and so on. It takes a lot of planning to get it right. The quality of the data association has been harmed as a result of poor information management. Increased data volume necessitates a lawful method of concentrating and processing data in a viable and effective manner. To create a classifier that can segregate data depending on its properties, one of the various machines learning software is used. The data collection has been divided into two or more classes. Medical data analysis and disease prediction are both aided by such classifiers. Machine learning is now so pervasive that it is possible to utilize it numerous times a day without even realizing it. For categorization, CNN uses both structured and unstructured data from a hospital. Other machine learning algorithms, on the other hand, only function with structured data and have a long computation time since they store all of the data as a training dataset and employ a complex calculating procedure. The first section covers the basics of disease prediction using classification methods like KNN and CNN.

The Convolutional neural organization (CNN) model is used to predict such anomalies, since it can accurately recognize information related to sickness forecast from unstructured clinical health records. However, if CNN uses a wholly related network structure, it consumes a significant amount of memory. Furthermore, an increase in the number of layers might lead to an increase in the model's intricacy research.

II. Literature Survey

Chunzhi Yi et.al [1] the increasing demand for fast and accurate gait-impaired disease diagnosis requires a real-time prediction of gait information in order to enable online information access to determining the disease progression. In addition, the wearable sensor-based information acquisition meets the new trend of take-home healthcare, the access to the great amount of data enables applying data-driven methods in this scenario. In this paper, we propose to use wearable Electromyography (EMG) and inertial measurement unit (IMU) sensors to make an ahead-of-motion prediction of basic gait information, including lower-limb kinematics and kinetics. Particularly, a novel long short term memory (LSTM) -based algorithm is trained to extract features and continuously predict lower-limb angles. Based on the predicted kinematics, the kinetics of lower limbs are calculated by a dynamic model of human segments. EMG signals recorded from nine lower limb muscles and IMU signals from each lower limb segment were collected for training the regressor. The experimental results with cross-validation among ten subjects have demonstrated the accuracy of the angle prediction and kinetics calculation. In addition, the optimal prediction time was exploited by testing the different sets of prediction time. The implication of this research work highlights the potential of continuous prediction of kinematics and kinetics, which provides fast and accurate access to basic gait information for smart healthcare applications.

According to Dhiraj Dahiwade et al. [2,] people suffer from various illnesses as a result of the natural environment and their lifestyle choices. As a result, anticipating sickness at an early stage becomes a substantial job. However, predicting the exact outcome based on the signs proves to be quite difficult for experts. The most difficult task is to have a realistic expectation of illness. To combat this problem, data mining plays an important role in predicting illness. Each year, clinical science sees a tremendous amount of knowledge development. Because of the increasing rate of information production in the clinical and medical care fields, the accurate assessment of clinical data that has benefited from early tolerant consideration has become more important. Information mining searches the vast amount of clinical data for hidden example data with the help of sickness information. They presented a general sickness forecast based on the patient's side effects. They use K-Nearest Neighbor (KNN) and Convolutional neural organization (CNN) AI calculations to forecast illness with pinpoint accuracy. Sickness side effects dataset was required for illness forecast. The living propensities for individuals and test results are considered for the precise expectation in this wide disease projection. The accuracy of the general infection forecast using CNN is 84.5 percent, which is higher than the KNN estimate. Furthermore, the time and memory requirements for KNN are higher than for CNN. Following a broad illness forecast, this framework is prepared to provide the risk of general infection, which is either low or high.

Domenico Formica et.al[3] This special issue on “Smart Sensors for Healthcare and Medical Applications” focuses on new sensing technologies, measurement techniques, and their applications in medicine and healthcare. We proposed this topic, being aware of the pivotal role that smart sensors can play for the improvement of healthcare services in both acute and chronic conditions as well as for prevention towards a healthy life and active aging. In this editorial we shortly describe the potential of smart sensors in the aforementioned applications, before moving on providing a general overview of the 24 articles selected and published in this special issue.

[4] Anjan Nikhil Repaka et al Data mining is a fantastic creation method that revolves around analyzing and unearthing massive amounts of data from a massive amount of data, which may be used in analyzing and sketching out designs for making business decisions. In the medical industry, information mining can be used to locate and extract important instances and data that can be useful in making clinical decisions. The investigation focuses on the conclusion of coronary artery disease based on previous data and information. To do this, Navies Bayesian is used to compose SHDP (Smart Heart Disease Prediction) in order to predict hazard factors related to coronary sickness. The rapid advancement of technology has resulted in a phenomenal rise in portable wellness innovation, which is one of the online applications. A normalized structure is used to collect the relevant data. The accompanying ascribes are gotten from the clinical profiles for anticipating the possibility of coronary illness in a patient, and these include: age, blood pressure, cholesterol, sex, glucose, and so on.

[5] Jianliang Gao et al. Studying the similarities between illnesses can help us investigate the neurotic aspects of complex illnesses, as well as provide strong reference material for constructing the link between new infections and infections that have been referred to, in order to develop feasible treatment plans. Most previous techniques either use a single similitude metric, such as semantic score or utilitarian score from a single information source, or use weighting coefficients to simply consolidate various measurements with various aspects to obtain the closeness of the illness.

Ping Xuan and colleagues [6] the discovery of infection- related microRNAs (sickness miRNAs) is a crucial step in the search for causative miRNAs and understanding disease pathophysiology. Foreseeing disease miRNAs can be done using two types of data: one that includes the relationships between miRNAs, illnesses, and infections, and the other that includes the properties of miRNA hubs. Data on miRNA similitudes, disease resemblances, and miRNA-infection associations may be found in the previous section. The data on the families and bunches with which miRNAs are associated is incorporated in the last option. Comparative infections are frequently associated with miRNAs with similar capacities and ascribes. However, a substantial portion of the current methodologies for illness miRNA forecasting are focused solely on the relationships between miRNAs and diseases. It will take some time to fully integrate the relationships and miRNA hub ascribes in order to identify more reliable up-and- coming infectious miRNAs.

According to Pengyao Ping et al. [7], a growing number of studies have shown that long-non-coding RNAs (lncRNAs) play key roles in a variety of important chemical cycles. Predicting potential lncRNA disease associations can improve how we understand the atomic instruments of human illnesses and aid in the discovery of biomarkers for infection detection, medication, and prevention. In this paper, they provided a creative model for inducing prospective lncRNA-illness affiliations based on a bipartite structure constructed in light of known lncRNA-sickness affiliations. They dismantled the properties of the bipartite organization in particular, observing that it firmly maintained power-law dispersion. A leave one-out cross-approval (LOOCV) system was also used to assess the presentation of our model, and the results revealed that our computational model fundamentally outperformed cutting- edge models, with AUCs of 0.8825, 0.9004, and 0.9292 for known lncRNAdisease affiliations obtained from the LncRNADisease data set, Lnc2Cancer data base, and MNDR data set, respectively. As a result, our methodology could be a fantastic addition to the field of biomedical investigation in the future. YI ZHANG and colleagues [8] Long non-coding RNAs (lncRNAs) have an impact on a variety of fundamental and important chemical cycles. Several lncRNAs have been linked to malignancies in some way. It is exhausting and time-consuming to use experimental and bioinformatics methods to recognize and define lncRNAs with disease-related tasks. As a result, an increasing number of experts have turned to computational tools as a means of uncovering previously unknown connections between lncRNAs and infections, specifically illnesses. They studied a novel two-stage expectation model (in particular DRW-BNSP) for constructing lncRNA-illness relationship in this review, given that there were few recognized lncRNA-sickness relationships out of huge cryptic affiliations: They used a Dual Random Walk (DRW) model in the first step to generate the essential forecast scores by walking on two reconstructed consolidated closeness networks; in the second stage, they used a Bipartite Network Space Projection (BNSP) model to make the essential forecast scores more paternal. In comparison to other best-in-class methods of similar type, our DRW-BNSP not only worked on new lncRNAs and detached diseases, but it also achieved higher AUC values of 0.9344 and 0.9432 on the first dataset (specifically Dataset1) and second dataset (specifically Dataset2) that we worked on. Furthermore, contextual analysis confirmed our DRW-prescient BNSP's steadfastness in predicting possible lncRNA-infection connections.

Ji-Ren Zhou and colleagues [9] Extra-long non-coding RNA (lncRNA)-disease associations are becoming increasingly important for developing therapeutics for complicated human infections. It's critical to distinguish between proof of lncRNA biomarkers and proof of lncRNA-illness associations for conclusions and treatment. In any case, traditional exploratory methods are time-consuming and costly. Computational algorithms used to predict lncRNA disease associations have access to large amounts of information contained in open natural data sets. They present a unique computational technique to predict lncRNA-illness associations in this review. To put it another way, a heterogeneous organization is built by coordinating the relationships between microRNA (miRNA), lncRNA, protein, drug, and illness. Second, high-request area protected installation (HOPE) was used to integrate hubs into a company. To prepare the expectation model, the turn timberland classifier was finally used. The area under the bend (AUC) of our approach achieved 0.8328 0.0236 in the 5-crease cross-approval test. They compare it to the other four classifiers and find that the suggested method outperforms other correlation algorithms. In any event, they came up with three different context analyses for

Mengjia Xu et.al[10] Characterizing the subtle changes of functional brain networks associated with the pathological cascade of Alzheimer’s disease (AD) is important for early diagnosis and prediction of disease progression prior to clinical symptoms. We developed a new deep learning method, termed multiple graph Gaussian embedding model (MG2G), which can learn highly informative network features by mapping high-dimensional resting-state brain networks into a low-dimensional latent space. These latent distribution-based embedding’s enable a quantitative characterization of subtle and heterogeneous brain connectivity patterns at different regions, and can be used as input to traditional classifiers for various downstream graph analytic tasks, such as AD early stage prediction, and statistical evaluation of between-group significant alterations across brain regions. We used MG2G to detect the intrinsic latent dimensionality of MEG brain networks, predict the progression of patients with mild cognitive impairment (MCI) to AD, and identify brain regions with network alterations related to MCI.

Hesham A et.al [11] Healthcare monitoring systems in hospitals and other health centers have witnessed throughout the last decade a tremendous growth and wireless healthcare monitoring devices with various technologies have become of great interest in many nations around the world. The proposed paper aims at integrating artificial intelligence technology, such as the neural networks and fuzzy system in a secure healthcare monitoring system in order to enable the system to work as a smart healthcare model that decides the priority by itself depending on the collected health parameters from the senor nodes. The proposed model consists of a trust environment that is responsible for collecting authenticated physiological data from patient's body which is then sent through GSM module to Azure IoT Hub where raw data is converted into linguistic representation, with the help of logic- based algorithm, which is trained in FBIS to get the status of the patient. The proposed system, then, provides reliable, accurate, secure and real-time patient monitoring. The following sections describe how the fuzzy based inference system (FBIS) can be integrated with a secure healthcare monitoring system to get the states of the patient and send it to the medical advisory for the preliminary precautions.

Lu Men et.al [12] Prediction of future clinical events (e.g., disease diagnoses) is an important machine learning task in healthcare informatics research. In this work, they propose a deep learning approach to perform multi-disease prediction for intelligent clinical decision support. The proposed approach utilizes a long short-term memory network and extends it with two mechanisms (i.e., time-aware and attention-based) to conduct multi-label classification based on patients' clinical visit records. The former mechanism (time-aware) is used to handle the temporal irregularity across clinical visits whereas the latter mechanism (attention-based) assists in determining the importance of each visit for the prediction task. Using a large clinical record data set (over 5 million records) collected from a hospital in Southeast China; they show that our proposed approach outperforms a variety of traditional and deep learning methods in predicting future disease diagnoses. They further study the impacts of different time interval choices for the time-aware mechanism and compare the performances of existing attention-based mechanisms with the one proposed in our study. Our work has implications for supporting physician diagnoses via the use of intelligent systems and more broadly for improving the quality of healthcare service.

Ajay S .Ladkat et.al [13] for processing on image, operations have to be performed on each pixel. If this operation is performed sequentially it will take too much time. So to reduce the time, there is need of parallel processing on all the pixels. So that instead of operating on each pixel one by one, operations on all the pixels is done parallel at a time. By performing parallel operations speed of processing is increased significantly as compared to sequential one. So it will also help to perform video processing in faster way. For parallel processing NVIDIA Graphics card is used. Parallel algorithm is performed on CUDAC platform.

Ajay S .Ladkat et.al [14] Diabetic Retinopathy is an abnormality of eye in which the retina of patient is affected due to an increasing amount of insulin in blood. The symptoms can distort or blur the patients vision and thus lead blindness. For automatic detection of exudates they first have to differentiate intensity levels of exudate and no exudate pixels.

Bikash Pradhan et.al [15] +e last decade has witnessed extensive research in the field of healthcare services and their technological up gradation. To be more specific, the Internet of +ings (IoT) has shown potential application in connecting various medical devices, sensors, and healthcare professionals to provide quality medical services in a remote location. +is has improved patient safety, reduced healthcare costs, enhanced the accessibility of healthcare services, and increased operational efficiency in the healthcare industry. +e current study gives an up-to-date summary of the potential healthcare applications of IoT- (HIoT-) based technologies. Herein, the advancement of the application of the HIoT has been reported from the perspective of enabling technologies, healthcare services, and applications in solving various healthcare issues. Moreover, potential challenges and issues in the HIoT system are also discussed. In sum, the current study provides a comprehensive source of information regarding the different fields of application of HIoT intending to help future researchers, who have the interest to work and make advancements in the field to gain insight into the topic. Muhammad Bilal Khan et.al [16] the future of dependable wireless communication will encompass a much eclectic range of applications. Not only are traditional telecommunication facilities such as text messaging, audio and video calling, video download and upload, web browsing, and social networking being improved but also a wide range of sensors and devices in the "Internet of things," such as "smart cities" and smart hospital applications are being adopted. Researchers are trying hard to ensure timely detection of various diseases anytime and anywhere. In this research, a portable and multifunctional software-defined radio (SDR) platform is designed to detect different activities of human life, in particular for the monitoring of health. The wireless channel state information (WCSI) in the presence of the human body is investigated to capture movements using different frequency bands and is the key idea of this work. Orthogonal frequency division multiplexing (OFDM) with 64 subcarriers and the magnitude and phase responses in the frequency domain are used to capture the WCSI of the activity. The design is validated through simulation and real-time experiments. However, it is widely accepted that simulation results fail to capture real-life situations. Extensive and repeated real-time experiments are carried out on the hardware platform to ensure that the activity is detected accurately. The results achieved by detecting hand motion activity ensure that the system is capable of detecting human body motions and vital signs.

Divya Ganesh et.al [17] the novel Corona Virus (COVID-19) is a pandemic of unimaginable proportion and magnitude that is posing a great challenge worldwide to the medical industry in the 21st century. It has completely changed the texture of life to a greater extent. The increasing number of victims succumbing to the disease has created an indelible fear in the minds of the people who are afraid to access even the basic healthcare facilities. This paper deals with the Automatic Health Machine (AHM) which uses IoT and Artificial Intelligence technologies to help users access medical facilities during a pandemic and medical emergency mostly in rural and urban areas. The AHM provides complete virtual health checkup, connects with the doctor or specialist online and books appointments for the swab test or ambulance in case of emergency based on the patient's condition, dispenses the swab test or emergency medicines and electronic prescription to patients for later reference. The services of the AHM are accessible to all individuals using "Smart Health Card". According to the Sustainable Development Goals (SDG- 3) proposed by the United Nations, the AHM ensures the wellbeing of all ages in society and increases the survival rate during unprecedented times like a pandemic/epidemic. We collaborated with industries and hospitals to understand healthcare/patients' requirements considering pandemic and post-pandemic. We conducted virtual workshops with the COVID-recovered patients and frontline nurses and doctors. As an overall outcome, the healthcare professionals feel the system can be adopted in an area where medical facility is not available immediately. Thus, our work has led to a patent being published in India and USA.

Divyashikha Sethia et.al [18] Patients with dispersed health records face the challenge of accessing readily available health history and mobility across different hospitals. It can hinder timely diagnosis and treatment, especially in the case of an emergency or for travelers. Cloud-based solutions have open challenges of interoperability and integration, higher challenges for security and privacy and may lack 24/7 support for the high availability of health history. Existing portable systems store limited health information for only a specific hospital and do not support mobility of patients across different hospitals. In this paper, we propose a next-generation portable Smart Health Record Management system with secure Near Field Communication (NFC)-enabled mobile devices to retain the dispersed health records on an S-MAPLE (Secure Mobility-Assisted Portable) health folder. It provides secure yet easy access to up to date health history and assists patient mobility across hospitals. An NFC based Host Card Emulation (HCE) mode maintains a software-based contactless mobile-based health wallet on the patient's mobile device. An authorized medical professional can access it directly and selectively with their mobile devices, over low energy wireless interfaces of NFC and Bluetooth. NFC provides secure proof-of-locality and ease of access.

Sandeep Kumar Polu et.al [19] the present health care system is, for the most part, in-hospital based and incorporates occasional visits that has turned as a monotonous activity for the patients. In this paper, a complete and integrated healthcare model is described enabling Remote Health Monitoring (RPM) patients to daily collect vital signs at home and sending them to caretakers using the Internet of Medical Things (IoMT). This enables doctors to screen patients at a distance and take occasional activities if there should be an occurrence of need. A set of health parameters has been identified i.e. Electrocardiogram (ECG), Pulse rate, Temperature, and Blood Pressure by using wearable sensors. These sensors are connected to an Intel Edison Board. Once the Intel Edison Board is connected to the internet, it collects data from sensors and sends to the server. The vital parameters can be visualized and monitored on any remote smart device including laptops or smartphones which are connected under the same network. The proposed demonstrate empowers users to enhance monitoring of health-related dangers and lessen hospital costs by gathering, recording, breaking down and sharing extensive health information continuously and productively. The possibility of this task came so to decrease the cerebral pain of patient to visit a specialist each time he has to check his pulse, heartbeat rate, temperature and so forth.

With the assistance of this proposal, the time of both patients and doctors are saved and doctors can also help in an emergency scenario as much as possible.

Hodjat Hamidi et.al [20] Internet of things is a new pattern in wireless communications of things. The basic theory of IoT is the comprehensive presence of different kinds of things in surrounding environment. The three main dimensions of data security in the Internet are integration, privacy and availability. One of the major tools for maintaining the security of Internet medical things is biometric technology. Biometric systems are used in different fields of the smart healthcare. In this regard, we also need a means for identifying people's identity based on their physical characteristics; the use of biometric data is absolutely critical for IoT functions. This paper proposes a continuous security solution based on IoT using biometrics for the smart healthcare technologies. In addition, joining biometrics to IoT brings concerns about the implementation of a user-friendly design. Thus, an IoT infrastructure based on biometrics including four levels is presented. The smart healthcare and IoT resulted in the emergence of a new standard in the applications of biometric data. In this paper, we present a new standard for applying biometric technology to develop smart healthcare using IoT which includes high capacity to access data in addition to being easy to use. In this paper, we reached a more secure way of accessing IoT based on biometrics and fast identity standard by which we can expect significant advances in smart healthcare systems.

III. Problem Statement

To detect the Various Diseases through the examining Symptoms of patient's using different techniques of Machine Learning Models.

IV. Exiting System

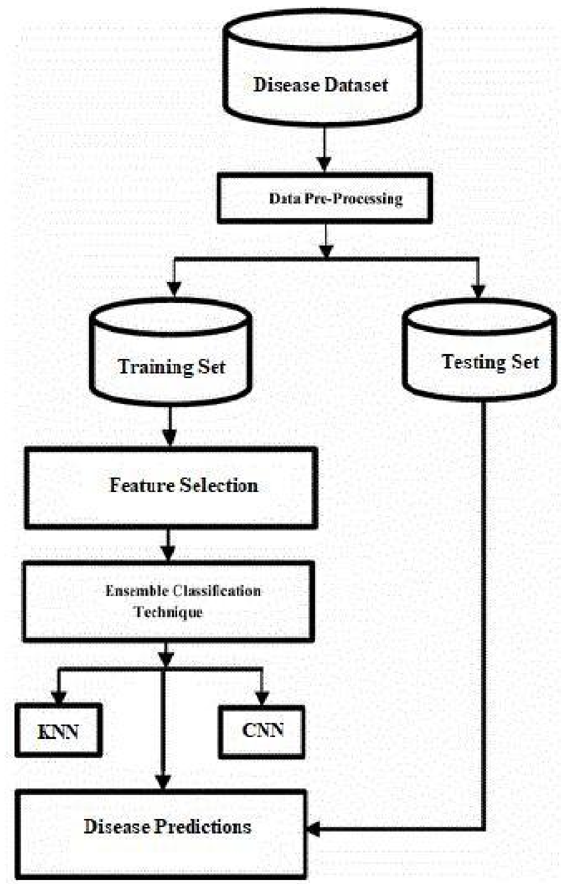

Figure 4.1: Architecture of Existing System

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Initially we take disease dataset from UCI machine learning website and that is in the form of disease list with its symptoms. After that preprocessing is performed on that dataset for cleaning that is removing comma, punctuations and white places. And that is used as training dataset. After that feature extracted and selected. Then we classify that data using classification techniques such as KNN and CNN. Based on machine learning we can predict accurate disease.

4.1 Data collection

Using the UCI dataset, Collection of medical data of patients with heart diseases is carried out. Throughout issues/matters are assumed for CAD and registered for angiography. Every patient's attributes are being assembled such as demographic, historic and laboratory features such as sex, age, hypertension, smoking history, diabetes mellitus, chest pain type, dyslipidemia, random blood sugar, low and high density lipoprotein, cholesterol, triglycerides, systolic and diastolic blood pressure, weight, height, BMI (body mass index), central obesity, waist circumference, ankle–brachial index, duration of exercise, METS obtained, rate pressure product, recovery duration with persistent ST changes, duke treadmill test and angiography result.

4.2 Prediction

With the launch of automated medical diagnosis system, there is high development in the medical domain and at the same time cost consumption has reduced. There are numerous factors prevailing for heart attack diagnosis and mostly patient's test records are being referred and analyzed for carrying out the diagnosis. For enhancing the diagnosis process, experience and knowledge of various medical experts/doctors as well as patient's medical screening data is being collected in databases, resulting in an extremely significant system. With blend of clinical decision support and computerized patient records, the medical faults can be reduced, patient's safety can be enhanced; variation in unwanted practices can be minimized thereby improvising throughout patient's results. In addition, by making use of heart disease levels predictions, a prediction algorithm is being established.

4.3 CNN

Neural networks are a set of algorithms, modeled loosely after the human brain that are designed to recognize patterns. They interpret sensory data through a kind of machine perception, labeling or clustering raw input. The patterns they recognize are numerical, contained in vectors, into which all real-world data, are it images, sound, text or time series, and must be translated.

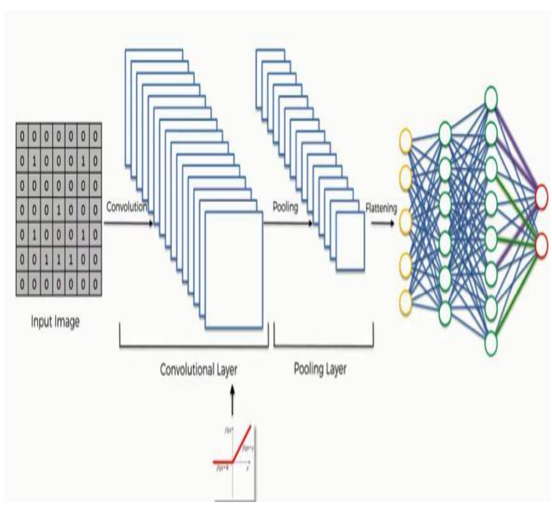

Figure 4.2: CNN Architecture

V. Conclusion

In light of AI calculations, we created a general disease forecast framework. We employed KNN and CNN algorithms to organize patient data since clinical data is becoming increasingly immeasurable, necessitating the use of existing data to predict careful sickness in light of side effects. As a result of providing the contribution as a patient record, we were able to obtain a precise general dis-ease hazard expectation, which helped us grasp the degree of illness hazard forecast. This framework may result in low time usage and insignificant cost for disease prediction and risk forecasting. In terms of precision and time, we may state that CNN out performs KNN.

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