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HOW AI CAN BE USED IN MEDICAL IMAGING

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ABSTRACT

For medical research, medical imaging is a visual technology and process for gen- erating images of tissues inside the human body in a non-invasive manner. It has two independent domains: medical imaging technology (MIT) and medical image processing technology (MPT). Among them, MIT applies natural physical phenomena, such as using light (optical correlation tomography (OCT)), sound (ultrasound (US)), mag- nets (Magnetic Resonance Imaging (MRI)), rays (X-ray, computed tomography (CT)), and so on. They are an essential basis for clinical analysis and judgment of treatment effect. In MPT, AI uses computer vision technology to optimize and assist in analyzing medical images, which provides more of a basis and quantitative analysis for doctors to assess patient status. Image enhancement, object detection and classification, image segmentation, image registration, image generation, and feature extraction are general MPT methods.

KEYWORDS: Digital Medicine, CT, MIT, US, X-Ray

INTRODUCTION

AI can improve the quality of images to help radiologists and doctors have a better reading experience. Furthermore, depending on image processing or deep learning algorithms, AI can also automatically or semi-automatically identify lesion areas in medical images, which assists doctors in detecting small lesions (such as lung cancer with high mortality) in their early stages and improves the five-year survival rate of patients [1-7]. At the same time, accurate AI-assisted annotation also reduces the heavy workload of doctors.

Given that AI has been widely used in many medical imaging domains, this section cannot cover all domains involving medical imaging in depth. This section focuses on the challenges and the corresponding solutions in the development of AI-assisted MPT in recent years (see Figure 1A, B). Moreover, we will focus on describing three AI-medical imaging domains (object detection and classification, image segmentation, and image registration) and briefly describe developments in other domains as well. This section is intended to be a clear demonstration of the current research status and highlights of artificial-intelligence-assisted MPT (Modeling and Predictive Techniques) for the readers.

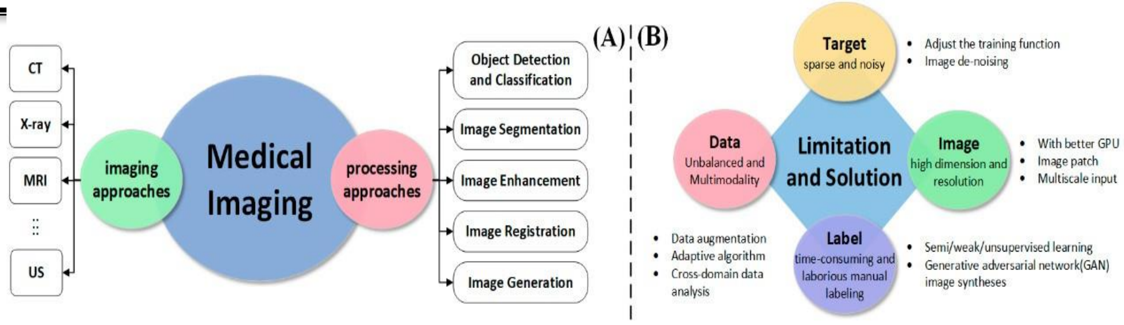

Figure 1. (**A**) Two independent areas of medical imaging. (**B**) Difficulties and solutions encountered in AI-based medical image processing technology [3-9].

DETECTION AND CLASSIFICATION

Object detection and classification is an important research field in MPT. It can provide specific location and disease details for doctors. Its accurate diagnosis reduces the workload of doctors and has a substantial auxiliary role for doctors in regard to analyzing images. Unlike natural images, medical images (e.g., MRI, CT, X-ray, etc.) are usually grayscale images, and there are two-dimensional slices and three-dimensional voxels. In addition, many lesions are only small areas and resemble surrounding tissue on images. Traditional medical detection and classification usually use traditional machine learning algorithms and hand-designed extracted features, but they are limited by prior knowledge [10-17].

In medical imaging, the detection and classification (recognition) of objects are usually staged due to the large image resolution. First, the region of interest (ROI, 2D) or volume of interest (VOI, 3D) is extracted through the detection algorithms and then input into the 2D/3D-based algorithms to output the classification result. [5] proposed two-stage deep learning models for detecting and classifying breast masses in X-ray images. They both use the Yolo detector with the CNN-based classifier and have good performance on the DDSM dataset. [12] proposed a CNN-based two-stage lung nodule detection algorithm for CT images, as shown in Figure 2. The algorithm first inputs the maximum intensity projection images of axial section slices in different thicknesses (1 mm, 5 mm, 10 mm, 15 mm). This data processing method has better performance in distinguishing nodules and vessels. The detection results are then input into a 3D CNN for false-positive reduction.

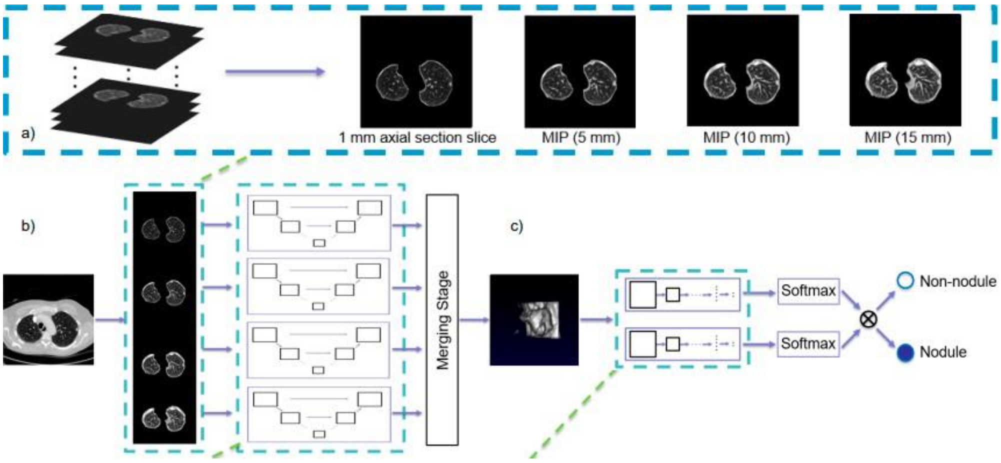

Figure 2. Architecture of a multi-stage 2.5D network for detecting lung nodules [12-23]. (**a**) is the maximum intensity projection image of axial slices of different thicknesses; (**b**) is the image merging process; (**c**) is the classification process.

Moreover, several algorithms forgo the multi-stage architecture characterised by error propagation, opting instead for end-to-end networks that facilitate training. [11] introduced a deep multi-task learning methodology for the detection of lung nodules in CT scans. The system incorporates lung parenchyma segmentation and nodule identification, utilising segmentation as an attention mechanism to enhance nodule detection. Reference [13] developed a densely linked 3D CNN to train the network using an end-to-end multi-task joint approach. This method demonstrated elevated detection accuracy on extensive CT imaging lung nodule datasets, including LUNA and LIDC. Furthermore, to clarify the unclear framework of small object identification, it does an additional study of these networks.

Given the insufficiency of annotations, suitable pre-trained models are crucial for classification efficacy due to their analogous data distributions. Consequently, transfer learning (TL) has significantly enhanced the performance of medical picture identification. [24] employed a transfer learning model to categorise brain tumours in MRI scans into three classifications: glioma, meningioma, and pituitary. The trials demonstrated that the pre-trained GoogleNet surpassed current models in brain tumour categorisation. [25] introduced a methodology utilising a pre-trained model (ImageNet dataset) and a Patch classifier to detect breast lumps (benign or malignant) in X-ray pictures. In comparison to previous patch-based methodologies used to the INbreast dataset, its test accuracy exhibits an enhancement of 8% (91.41% to 99.34%), which is statistically significant, Medical Image Segmentation.

Image segmentation is a prominent subject in image comprehension and a crucial technique in medical image processing. Image segmentation partitions the entire image into many areas, wherein the elements within each region exhibit analogous qualities. In medical imaging, picture segmentation can delineate areas of interest (ROIs), such as lesions, to differentiate between background and tumours. It can see and quantitatively analyse patient tumours, significantly aiding clinicians in evaluating patients' conditions and tumour stages.

Figure 3 represents the fundamental structure of picture registration. Typically, picture registration involves four primary steps: (1) Feature points are derived by extracting characteristics from two images; (2) a similarity matrix is established by identifying corresponding feature point pairs through similarity assessment; (3) the parameters for image space coordinate transformation are ascertained via the matched feature point pairs, where the maximum relevant point is identified based on the optimisation criterion, allowing for the resolution of unknown parameters within the transformation model; (4) image registration is executed using the optimal coordinate transformation parameters to achieve inter-image registration alignment [26-35].

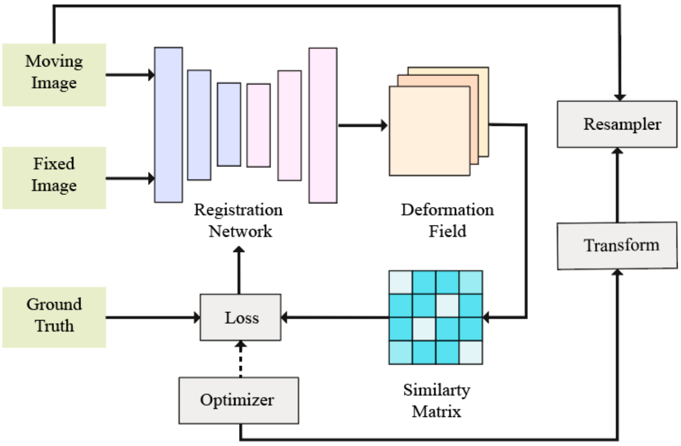

Figure 3. Image registration core framework.

ADDITIONAL APPLICATIONS OF AI IN MEDICAL IMAGING

Image generation and improvement: The synthesis and improvement of images across many medical imaging modalities and procedures is a prominent research focus in radiation oncology and radiology. Nonetheless, medical images possess distinct characteristics. It is focused on the following aspects: (1) Robust privacy: Medical data pertaining to patient confidentiality cannot be disclosed, leading to a limited number of medical datasets; (2) intricate structure: Unlike natural images, medical image data are complex and heterogeneous, often necessitating specialised knowledge; (3) challenging acquisition: Specific image acquisition is often impractical, resulting in increased patient exposure to ionising radiation and incurring additional labour and costs. Consequently, several academics have suggested various strategies for image creation and augmentation, with the most prevalent being the generative adversarial network (GAN), which seeks to optimise certain clinical processes by circumventing or substituting specific imaging techniques [36-42].

Incorporating a Generative Adversarial Network into a progressive genetic algorithm to swiftly generate ischaemic heart disease pictures that closely resemble authentic ones. [34] proposed a diabetic retinopathy generative adversarial network (DR-GAN) to generate high-resolution fundus pictures that can be altered with any grade and lesion information. [35] introduced a multi-task coherent mode transferable GAN for unsupervised brain MRI synthesis. It efficiently mitigates issues related to patient discomfort, high expenses, and scanner unavailability. Remarkable outcomes have been attained in picture synthesis and enhancement through the innovative application of deep networks across many tasks. One might anticipate a further rise in the quantity of forthcoming missions. Automated report generation: Radiology reports function as the principal mode of communication between radiologists and referring doctors. Writing a clear, accurate, succinct, and comprehensive report is a significant challenge for radiologists, particularly in poor countries, owing to their substantial workload, limited time, and weariness. Statistics indicate that around 4% of reports authored by radiologists contain mistakes in the interpretation of discernible visual patterns, including lexical ambiguity, double negatives, and undefined modifiers, among others. [17] All of these factors may mislead clinicians when interpreting the report. Consequently, much research has been conducted on approaches for the automatic generation of reports to optimise clinical operations, thereby minimising time, mistakes, and expenses. [24] provided a system for the automated development of AlignTransformer reports, which may be utilised to calibrate transformers that mitigate data bias concerns and model extensive sequences for the production of medical reports. [13] introduced a cross-modal memory network (CMN) to improve the encoder-decoder framework for radiology report generation, wherein the shared memory was constructed to document the alignment between images and text, tackling the multimodal mapping of visuals and text and its application for enhanced report generation.

Image acquisition: The exponential growth of medical data has become content-based image retrieval (CBIR) a focal point of study. It is a method for information extraction from extensive datasets. It collects characteristics from input photographs and rapidly searches the image library for analogous illness histories inside the feature space to aid clinical diagnosis. The primary challenge of CBIR now lies in the significant disparity in content characteristics of medical pictures acquired from various imaging systems, together with the successful extraction of features from these images and their association with meaningful ideas. The primary difficulty in the advancement of CBIR approaches is to derive effective feature representations from pixel-level data and correlate them with significant ideas. The capacity of deep CNN models to acquire intricate characteristics at several levels of abstraction has captivated the CBIR community.

Similar pictures are obtained by an image feature generating approach and network community identification technology, enabling the extraction of analogous images from extensive X-ray databases. [14] introduced a triplet hashing (ATH) network to maintain categorisation, ROsI, and few-shot information through the learning of low-dimensional hash codes. This approach may efficiently direct medical pictures using medical information and mitigate the issue of sample imbalance. [15] introduced a depth map-based multimodal feature embedding (DGMFE) framework for medical image retrieval that utilises visual similarity across pictures to construct a multimodal graph model, hence uncovering relevant information for image retrieval tasks.

Despite several instances of research on content-based picture retrieval now available, there is a deficiency of effective practical implementations. In comparison to accomplishments in other domains, a considerable duration will be required.

In the future, the diagnosis of artificial intelligence-assisted medical imaging will increasingly become automated and user-friendly, providing physicians and patients with more precise quantitative findings, evolving in three distinct ways. Image processing technology will become quicker and more precise, aiding physicians in a broader range of diagnosis. The integration of quantum computing with AI medical imaging, advancements in hardware, and the availability of open-source datasets for diverse diseases all enhance the progress of MPT and establish a research foundation for the ongoing investigation of other disease kinds. Secondly, deep learning and artificial intelligence persist in investigating semi-supervised and unsupervised methodologies. The use of minimal annotation levels decreases labour expenses while diminishing the barriers to research, enticing more academics to investigate medical imaging and perpetually enhancing the efficacy of non-massive data-driven approaches. It can effectively aid physicians in diagnosing while minimising expenses. The integration of imaging technology with various clinical contexts, alongside the amalgamation of additional data, facilitates the transformation of results from a singular image domain to patient-specific information [43-55]. This includes pre-diagnostic, intra-diagnostic, and prognostic data, thereby equipping physicians with more comprehensive and precise informational recommendations for consideration.

THE UTILISATION OF AI IN ELECTRONIC HEALTH RECORDS

CHARACTERISTICS OF EHR DATA

Electronic health records (EHRs) are digital repositories of health and medical information that document a patient's medical history, drug administration records, test findings, clinical notes, and treatment expenses. EHRs effectively present the outcomes of patient care and assessments. Simultaneously, they suggest the causal causes of certain diseases, the adverse effects of medications, the implicit connections among diseases, and the correlation data between diagnostic results and diseases [16], among others. The advancement of machine learning algorithms and big data technology facilitates the utilisation of EHR data as a substantial resource for constructing classification or prediction models in AI-enhanced medical applications, establishing a basis for the development of clinical decision support systems and personalised precision medicine. EHR data has increasingly been crucial to AI-assisted auxiliary medical applications in health care research [56].

Patient representation utilising discrete medical concepts entails the extraction of patient characteristics from specific entities, like international classification of diseases (ICD) codes or medical documentation. The primary challenge of this sort of patient representation is the extraction of relations from high-dimensional medical text data and the alignment of medical codes across various standards. [45] established a natural language processing (NLP) framework utilising UMLS MetaMap and BioWordVec, which generates patient representations from discrete EHR data and subsequently employs clustering and association rule mining to identify patient clusters and relationships among patient attributes. This research identifies connections among different symptom kinds in breast and colorectal cancer patients by utilising the framework. [36] presents a knowledge graph system for electronic health record (EHR) data that converts EHR data into a semantic, patient-centered information model, enabling reasoning through semantic rules to uncover significant clinical results and overlooked clinical information within EHR data. This study discovers 2,774 patients who fulfilled the diagnostic criteria but were overlooked, so efficiently using the latent, underutilised information within the EHR data.

The patient depiction utilising time series medical data is intended to depict the patient through time series vital signs data, including respiration rate, heart rate, and blood pressure. The challenge of this representation is in developing a model that autonomously infer correlations between patient indicators and illness symptoms across various time periods. Simultaneously, the issues of unequal sampling and asynchronous sampling of time series data must be considered.

A bidirectional deep learning model (BRLTM) is designed to consolidate diagnosis codes, procedure codes, drug codes, and clinical records in [41]. Subsequently, it analyses the temporal relationships of information to derive patient representations and forecast depression. [42] introduces a predictive model utilising the attention mechanism, which acquires patient representation by interpreting contextual information and the temporal relationships of illness codes in electronic health record (EHR) data, thereby facilitating disease diagnosis in patients. The model presented in this research demonstrates exceptional prediction efficacy with datasets pertaining to heart failure, diabetes, and chronic kidney disease. A temporal tree model utilising temporal hierarchical representation and temporal co-occurrence is presented in [18] to represent patients, with doc2vec embedding technology employed to augment patient representation, hence facilitating the calculation of patient similarities.

Patient representation utilising multimodal data necessitates the integration of diagnostic codes, medical texts, vital signs, medical pictures, and additional data from various modalities to articulate patient features. The primary challenge is in addressing the variety of data and acquiring associative learning from EHR data across several modalities [57-66].

[12] amalgamates diverse heterogeneous data, including diagnostic ICD codes, medication timestamps, and medical picture descriptions to delineate patient characteristics. It subsequently employs gradient boosting, multi-layer perceptron, and convolutional neural networks-long short-term memory (CNN-LSTM) models to facilitate the diagnosis of sepsis. [18] employs a matrix-based representation to analyse the multi-source structure of clinical EHR data and utilises CNN to rapidly extract patient feature representations for the identification of Kawasaki disease patients from incomplete data. A collective hidden interaction tensor decomposition model (cHITF) is introduced in [19] to ascertain the relationship between diagnostic and medication data across several modalities, facilitating the simultaneous learning of patient representation. Figure 4 illustrates the precise structure of cHITF. Experiments utilising the MIMIC-III dataset demonstrate that the patient phenotypes derived from cHITF have greater therapeutic relevance.

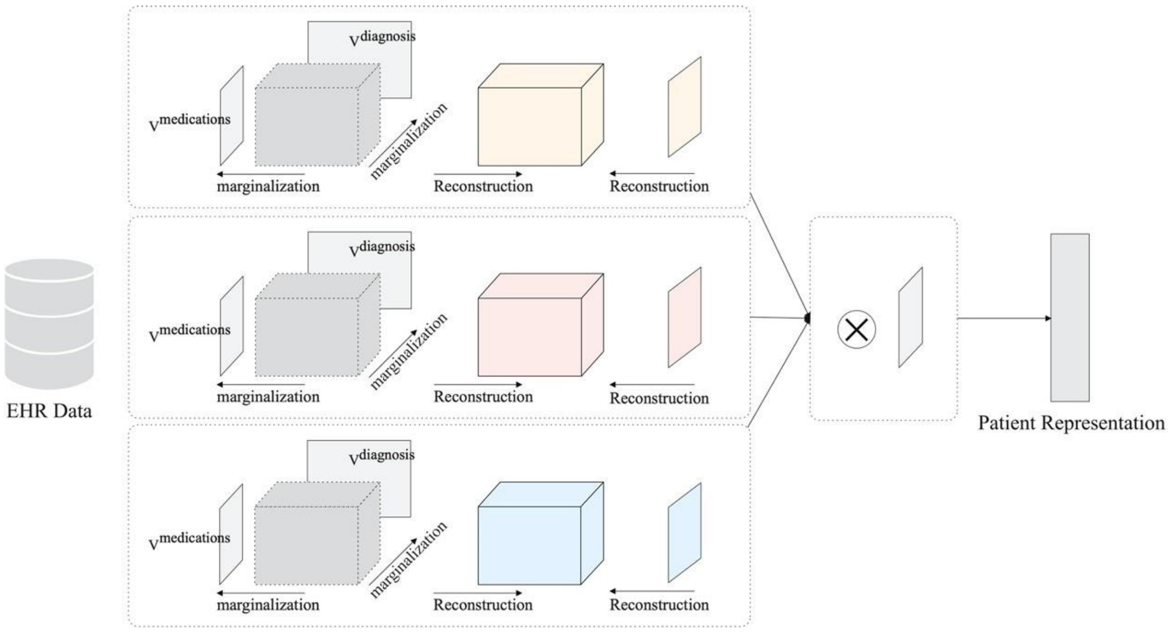

Figure 4. Collective hidden interaction tensor decomposition model [67].

DIAGNOSIS AND PREDICTION OF DISEASES UTILISING EHR DATA

A significant application of EHR data in healthcare is disease diagnosis and prediction. Utilising EHR data for illness detection can significantly enhance diagnostic accuracy and predictive capabilities, facilitating disease prevention through early alerts, streamlining clinical decision-making, and decreasing medical expenses. Some studies utilising EHR data for disease diagnosis and prediction have accomplished this through patient representation [41]. Alternative studies have attempted to directly extract pertinent illness characteristics from electronic health record data to classify or forecast the condition. This research may be categorised into three groups based on the EHR data utilised: disease diagnosis and prediction using discrete medical concepts, time series medical data, and multimodal data [68-74].

Disease diagnosis and prediction utilising discrete medical concepts frequently encounter the issues of high dimensionality and sparsity. [20] introduces a semi-supervised multi-task learning approach that considers the prediction of the glomerular filtration rate (eGFR) state at a specific time point as a task, utilising eGFR, pathological classification, and other structured electronic health record (EHR) data to forecast the short-term progression of chronic kidney disease.

(2) The literature [21] presents a model utilising third-order tensor decomposition to analyse ternary correlations that incorporate supplementary clinical attributes or temporal features from electronic health record diagnostic data, facilitating the prediction of chronic disease incidence. [75] employs an attention-based Bi-LSTM model to extract temporal information from time series EHR data for predicting cardiovascular disease risk in patients.

(In illness diagnosis prediction utilising multimodal data, common instances include the integration of physiological signal characteristics with EHR structure data and the amalgamation of medical images with EHR structural data to facilitate disease diagnosis or prediction. Advanced signal processing methodologies, including Taut String estimation and dual-tree complex wavelet packet transform, are employed to extract features from ECG data for predicting the beginning of problems in cardiovascular surgery. Furthermore, chest X-rays and clinician confidence levels in the diagnosis served as indicators of label uncertainty for diagnosing acute respiratory distress syndrome (ARDS) [76-79].

ALTERNATIVE UTILISATIONS OF EHR DATA

An essential application of EHR data in AI-enhanced intelligent medical systems is the prediction of hospital resource utilisation. [22] employs Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) to capture temporal relationships within clinical data and implements a convolutional multimodal architecture to extract characteristics from patients' health records. This reference employs various word embedding techniques, including Word2Vec and FastText, as well as their integration, to derive low-dimensional representations of patients, facilitating predictions of patient mortality and hospitalisation duration while optimising hospital resource management. [44] employs a fuzzy-division-enhanced local weighted decomposition machine to analyse the hospitalisation features of patients inside electronic health record data, while also accounting for the likelihood of patient readmission to optimise medical resource management.

An additional application of EHR data is the forecasting of patient death and clinical outcomes, assisting clinicians in determining the appropriate cessation of therapy to successfully mitigate overtreatment. A bidirectional variational recurrent network randomly reiterates the imputation of absent data in the electronic health record and encapsulates the uncertainty in the distribution of imputed values. Consequently, it can leverage the uncertainty to modify the hidden state in the GRU unit to facilitate the prediction of patient mortality. [23] presents a deep learning-based embedding approach that develops a multi-level corpus for categorical variables in electronic health record data. The sequence of cross-domain interaction ranks categorical variables in EHR data, enabling the sequential learning of attribute-level representations of cancer patients and the prediction of their clinical endpoints.

Moreover, the EHR data can facilitate the computation of patient similarity and the identification of analogous patient groups. [18] derives patient representations through the application of the time tree model and doc2vec embedding technology, facilitating the computation of patient similarities. [24] formulates a probabilistic model utilising Gaussian mixture models to identify patients with particular clinical traits and employs hierarchical clustering, underpinned by Kullback–Leibler divergence, to establish a resilient low-dimensional space for the identification of patient groups with analogous health conditions. Comparable or comparable therapeutic treatment protocols may be administered to patients within the same or similar cluster.

OBSTACLES ENCOUNTERED BY EHR DATA-ENHANCED HEALTHCARE

Numerous instances of research and applications utilising EHR data in health care exist within academia and industry; nevertheless, researchers frequently encounter obstacles related to privacy, heterogeneity, time series, high dimensionality, and sparsity when employing EHR data to support medical treatment. EHR data encompasses extensive patient privacy information and includes health data from many sources, types, and modalities. An inpatient's electronic health record may document structured diagnostic codes, time series vital sign data including blood pressure and heart rate, as well as unstructured medical text data encompassing diagnostic analysis and clinical descriptions, together with unstructured medical imaging data such as CT and MRI scans. Concurrently, patients often fail to complete all testing and treatment procedures, resulting in EHR data exhibiting characteristic high-dimensional traits. Figure 12 illustrates prevalent solutions in research.

THE UTILISATION OF ARTIFICIAL INTELLIGENCE IN HEALTHCARE MANAGEMENT

With the assistance of 5G communication technologies, intelligent IoT terminals are progressively integrating into the medical sector. Intelligent wearable gadgets can assess blood pressure, heart rate, and blood oxygen levels, while other wearable technologies can track the user's physiological state in real-time. In health management, wearable devices can gather real-time monitoring data from consumers and subsequently transmit the data to the backend for storage. Following the pre-processing of the raw data, the health management system can employ AI techniques to analyse and extract insights from the data, subsequently producing analytical reports [75]. Via electronic reports and in data visualisation, the analytical outcomes are communicated to physicians and users, aiding doctors in understanding the users' health statuses, as seen in the framework in Figure 13. The health management system can monitor users' physical conditions in real-time and eliminates the necessity for in-person consultations with doctors, thereby extending medical resources to remote places and conserving users' time in obtaining medical care. During the global COVID-19 pandemic, telemedicine via wearable gadgets can address the issue of patient access to healthcare. The data collecting and transfer method entails the risk of data leakage, jeopardising consumers' privacy [76-82]. This section will explicitly address several areas of health management, including wireless mobile therapy, medical data fusion and analytics, medical data privacy protection, and health management platforms.

WIRELESS MOBILE THERAPY

Wireless devices, such smart bracelets, wristbands, and subcutaneous sensors, are intimately integrated into our lives, positioned on specific body areas to monitor various performance indicators. Users can utilise various wearable devices as necessary to control conditions such as diabetes and epilepsy, while also monitoring their physical health; these devices can even ascertain COVID-19 infection status using specific data indicators. Wireless devices continuously generate monitoring data and transfer information such as blood pressure, temperature, and oxygen saturation to the background via communication techniques like Bluetooth and Wi-Fi, which researchers can utilise for data analysis [83-88].

Wearable devices manifest in multiple forms. Textile-based wearable systems, featuring sensors embedded in garments and positioned around the user's waist, can monitor heart rate fluctuations for the assessment and analysis of cardiovascular illnesses. Body temperature detection can also be accomplished with a sensor positioned near the skin. Biofluid-based wearable devices can conduct disease surveillance by analysing the composition of significant secretions, like sweat and tears, produced by the body. A wearable device for colorimetric sweat sensing has been created in the paper for detecting chemical composition [27]. The wearable gadget facilitates prompt medication management and administration for disease treatment by monitoring physiological markers such as body temperature, heart rate, and perspiration. For instance, the system facilitates the timely administration of medication to the eye for the treatment of glaucoma.

Wearable technologies, beyond individual health indicator monitoring, can amalgamate diverse data to facilitate the surveillance of specific diseases, continuously assess patients' physical status, and ensure life safety. By monitoring the wearable gadgets utilised by pre-diabetic patients, the patients’

INTEGRATION AND ANALYSIS OF MEDICAL DATA

In wireless mobile diagnosis and therapy, wearable devices monitor several physiological signs and transfer the data to a management platform for analysis. Nonetheless, owing to the extensive range of wearable devices from various manufacturers, the integration and pre-processing of the acquired patient data is a crucial step prior to data mining. The challenges encountered in the fusion and pre-processing of medical data encompass data noise, absent data, and data shortage. The primary solution is to address the issue of limited datasets by data augmentation. The study [48] examines textual data to forecast patients with unfavourable visual prognosis by integrating electronic health records and unstructured text data.

To enhance patient care and thoroughly derive valid insights from the data, the processed information must be analysed and mined. Presently, the majority of researchers in data analysis and mining predominantly employ machine learning and deep learning techniques, but some utilise association rules for data extraction. The research [48] examined three artificial intelligence algorithms: fuzzy logic, genetic algorithm, and hierarchical analysis. Clustering, classification, and association rule algorithms were examined to derive valuable insights from health data. [9] introduced a deep learning-based approach for medical data mining that discretises intricate medical data, examines the direct mapping relationships using convolutional neural networks, and subsequently extracts the association rules among the data.

The raw data obtained from wearable devices mostly consists of individual numerical values, while data acquired from medical imaging techniques, such as CT scans, are represented as black and white two-dimensional images. The raw facts are not conducive for physicians in diagnosing by direct observation. Presenting this data as graphics or 3D images might be more intuitive. Displaying the outcomes of data analysis and mining through a visual interface would enable the patient to distinctly observe their physical condition and bodily changes. The research [30] examined visualisation strategies for 3D medical images and summarised the available open platforms for medical image visualisation. [14] examined visualisation tools in the healthcare sector, outlined the rationale and importance of visualisation, and contrasted the various types and benefits of different visualisation tools. The paper provides examples of healthcare data visualisation and elucidates its application within the healthcare sector.

The utilisation of visualisation technology in medicine offers significant advantages for patients and physicians; yet, due to the sensitive nature of medical data, it is imperative to safeguard patient privacy throughout the visualisation process. The obstacles encountered in medical data visualisation primarily consist of many sources and modalities of medical data, a scarcity of public datasets, patient privacy concerns, and ethical considerations. Healthcare Management System. Patients want a comprehensive health management platform to connect with their doctors, whether through wearable devices for body monitoring and disease management or telemedicine for online access to medical care. The health management platform serves as a conduit between data, physicians, and patients, collecting data from wearable devices and presenting the results of data analysis and mining in a visual format. This enables physicians and patients to access and comprehend their health conditions and facilitates timely communication between them.

A comprehensive health management platform for a specific disease must encompass data collecting, data storage, data analysis, and data display of results. [52] suggested an open-source software architecture for a health management platform encompassing data collection, transmission, analysis processing, and visualisation. The platform aggregates data from wearable devices and using encryption technology to transmit the data to backend storage. It integrates historical data to establish correlations with certain diseases, from which the data are analysed and extracted using machine learning techniques, and the analysis results are subsequently communicated to users via the platform. [35] develops a diabetes health management platform utilising GCM, enabling patients to monitor real-time blood glucose fluctuations through wearable monitoring devices. The collected data is transmitted to the platform for analysis, which subsequently offers dietary and medication recommendations based on the results.

In light of the global COVID-19 pandemic, online access to medical care emerges as a superior approach. Home isolation permits health testing via IoT devices, and communication with clinicians is facilitated by a home health management platform. The paper [136] developed a doctor-patient management platform that monitors fundamental patient data via medical collection devices, transfers the data to a data warehouse for storage post-collection, and facilitates rapid updates to address the issue of incomplete patient data, thereby uniting hospitals, physicians, and patients.

As society evolves, communal living has become a prevalent practice among humans. It has become customary for the elderly to age within the community. A Colombian healthcare institution's digital health platform amalgamates operational, clinical, and business data sources with sophisticated analytics to enhance decision-making for population health management. [37] presents a community-oriented aged care model that integrates children, the community, and emergency services by gathering health data from elderly individuals to establish a network of positive relationships.

In the future societal evolution, as individuals increasingly prioritise physical health and confront significant population ageing, the use of wearable technologies for health management and eldercare will emerge as a principal developmental trajectory. Employing artificial intelligence to facilitate health management not only oversees consumers' monitors physical health in real-time while also facilitating rapid access to patient information for physicians. The advent of telemedicine allows individuals in rural regions to access quality medical services, while community management tools are increasingly compatible with the novel aged care model. In the advancement of health management, numerous interconnected factors are involved, presenting various challenges beyond the development and communication of wearable devices. These include difficulties in data storage, preprocessing, and mining, the judicious application of visualisation tools to present analytical outcomes, and, crucially, the safeguarding of data security and user privacy, along with the complexities of information security [51].

THE UTILISATION OF ARTIFICIAL INTELLIGENCE IN MEDICAL ROBOTICS

Medical robots originated from the inaugural neurosurgical brain biopsy conducted in 1985. Over the subsequent three decades, advancements have led to the development of medical robots for laparoscopic surgery, prostate biopsy, ophthalmic surgery, and various other medical disciplines. Prominent surgical robots, including Da Vinci, Verb, and MAKO, have gained widespread utilisation globally. Medical robots incorporate instruments such as small cameras, surgical sutures, and robotic arms, offering advantages of high precision, adaptability, and control. They have predominantly addressed the deficiencies of conventional manual surgery through machine automation, enabling precise positioning and diagnosis, remote treatment, and superior patient care, while substantially alleviating the workload of healthcare professionals in diagnosing and treating patients.

Artificial intelligence robots are aiding physicians in executing intricate tasks, ranging from positioning and diagnosis to surgery, so enhancing the intelligence and scientific rigour of medical care and offering greater ease to humanity [39]. Recent research can be categorised into three primary types based on application depth: surgical robots, rehabilitation robots, and intelligent assistive robots. Surgical robots, due to their accurate positioning and absence of physiological tremors and weariness, facilitate reduced surgical trauma and minimise postoperative problems. Their application range is extensive, encompassing orthopaedics, cardiology, gastroenterology, gynaecology, and neurosurgery. Examples comprise the swan for joint replacement; Tumai, China's inaugural comprehensive coverage of the thorax, abdomen, and pelvis; and the Mona Lisa for prostate puncture. Nonetheless, current surgical robots are costly cumbersome, necessitate human oversight, and have not yet attained full autonomy.

Surgical robots have not addressed prognostic challenges in surgery, including rehabilitative training. The advent of rehabilitation robots facilitates the assistance of patients in performing rehabilitation exercises. This entails the prolonged and efficient recurrent training of patients' impaired limbs via limb tracking, motion trajectory forecasting, guidance, and propulsion to fulfil therapeutic objectives. Miguel Nicolelis and colleagues in the United States employed three primary training technologies—brain-computer interfaces, lower limb exoskeleton rehabilitation robots, and virtual reality—to facilitate substantial recovery in spinal cord injury patients, transitioning them from complete paralysis to lower limb muscle and sensory function. Mehrabi and colleagues developed a lightweight, secure, friction-driven dual-degree-of-freedom ankle rehabilitation robot, compatible with any mobile platform, to assist patients in ankle rehabilitation exercises; the portable planar passive rehabilitation robot PaRRo can facilitate the patient's arm rehabilitation treatment [42]. Regrettably, rehabilitation robots pose privacy and security concerns related to health records, genetic information, and additional data.

In tasks like disease detection and remote help, auxiliary robots can facilitate diagnostic support through visualisation, high precision, and real-time capabilities, significantly diminishing the repetitive burden of manual positioning and classification. The blood collection accuracy of China's inaugural blood collection robot is 92%, comparable to that of medical personnel. Nonetheless. The interpretability of prospective artificial intelligence models is limited, and there are inherent hazards when robots aid in diagnosis and therapy; thus, their outcomes may only serve as supplementary references for physicians. Moreover, both patients and physicians exhibit intrinsic scepticism regarding artificial intelligence in diagnostic and therapeutic technologies [89].

Deep learning is becoming increasingly pivotal in the advancement of robotics. Object identification, tracking, and picture segmentation of surgical targets are critical components of surgical robots executing surgical procedures. The integration of deep learning algorithms for computer vision, pattern recognition, and real-time decision-making with clinical medicine allows AI robots to excel in pre-operative planning and intra-operative guidance, enabling them to execute medical tasks with high precision and safety [43]. Deep convolutional neural network architectures, including AlexNet, ResNet, and DenseNet, enhance the interpretability of feature patterns and improve the accuracy of image categorisation. Figure 14 delineates the predominant artificial intelligence methods utilised in AI robotic systems in recent years, categorised into four dimensions: target tracking, positioning, control, and human–computer interface.

ARTIFICIAL INTELLIGENCE TECHNOLOGY UTILISED IN ROBOTIC SYSTEMS.

Regarding tracking and positioning, deep learning algorithms surpass conventional object tracking methods reliant on local optimisation. Current deep neural network algorithms, when integrated with micro cameras in robots, may swiftly and precisely identify and pinpoint moving equipment and tools, thereby efficiently identifying, locating, and segmenting target objects in intricate images, such as U-net and Attention mechanisms. [44] employed a weak supervision approach to autonomously produce binary annotations for delineating tool space information within the dataset and achieved real-time tracking of surgical tools utilising LSTM and CNN technologies. This technique significantly enhances surgical precision. [45] suggested a neural network utilising the LSTM-RNN architecture, which learns and extracts visual geometric information via supervised learning techniques to provide precise force magnitude estimation. Experimental findings indicate that this strategy attains a recall rate of 0.98 and an average root mean square error of merely 0.02 N.

Algorithms like deep convolutional neural networks (DCNN) and recurrent neural networks (RNN) are employed to extract data for non-linear kinematic modelling, facilitating auxiliary segmentation and detection of intricate surgical processes. Deep learning models, including multi-scale LSTM (MS-LSTM) Duelling [54], are employed to forecast multi-joint motion trajectories and minimise motion discrepancies between the user's arm and the robotic arm, thereby effectively assisting patients in bilateral rehabilitation training. Technologies include motion planning, control, and perception can facilitate the planning of robotic arm movements for automatic correction in surgical trajectories. Reinforcement learning models are employed for analytical modelling to effectively illustrate intricate procedures, like automatic suturing of soft tissue and high-precision spinal needle injection. [55] employed the Deep Reinforcement Learning approach to acquire tensioning strategies within a simulated environment for tissue cutting or removal, successfully discerning the patterns of surgical scissors and tissue. [90] employed an artificial neural network architecture to proficiently execute human-robot control of predetermined surgical motion trajectories. [60] employed convolutional neural networks and stacked denoising autoencoders (SDAE) to execute intricate gesture categorisation tasks with elevated accuracy, hence enhancing the safety and dependability of robotic gesture control.

CONCLUSIONS

In conclusion, artificial intelligence has several uses in medical aid and is assuming an increasingly significant role. This study delineates the historical progression of artificial intelligence, specifically its evolution and present state in medical assistance. It offers a comprehensive examination of AI technologies employed in healthcare, encapsulates the research accomplishments of artificial intelligence in medicine across six principal domains (namely genomics, drug development, medical imaging, electronic health records, health management, and medical robotics), and evaluates the challenges and prospects confronting AI in medical assistance. Despite the various problems AI technology encounters in the medical domain, it also presents significant developmental prospects. Artificial intelligence offers supplementary services for humans. It can solely assist physicians, not supplant them. Currently, artificial intelligence functions merely as a fundamental, repetitive, and substitutable technical service, mostly directed towards laboratories and their scientific research endeavours.

REFERENCES

[1] Maddireddy, B.R. and B.R. Maddireddy, Adaptive Cyber Defense: Using Machine Learning to Counter Advanced Persistent Threats. (2023). International Journal of Advanced Engineering Technologies and Innovations, 1(03): 305-324.

[2] Maddireddy, B.R. and B.R. Maddireddy, AI and Big Data: Synergizing to Create Robust Cybersecurity Ecosystems for Future Networks. (2020). International Journal of Advanced Engineering Technologies and Innovations, 1(2): 40-63.

[3] Maddireddy, B.R. and B.R. Maddireddy, AI-Based Phishing Detection Techniques: A Comparative Analysis of Model Performance. (2022). Unique Endeavor in Business & Social Sciences, 1(2): 63-77.

[4] Maddireddy, B.R. and B.R. Maddireddy, Blockchain and AI Integration: A Novel Approach to Strengthening Cybersecurity Frameworks. (2022). Unique Endeavor in Business & Social Sciences, 5(2): 46-65.

[5] Maddireddy, B.R. and B.R. Maddireddy, Cybersecurity Threat Landscape: Predictive Modelling Using Advanced AI Algorithms. (2022). International Journal of Advanced Engineering Technologies and Innovations, 1(2): 270-285.

[6] Maddireddy, B.R. and B.R. Maddireddy, Enhancing Endpoint Security through Machine Learning and Artificial Intelligence Applications. (2021). Revista Espanola de Documentacion Cientifica, 15(4): 154-164.

[7] Maddireddy, B.R. and B.R. Maddireddy, Enhancing Network Security through AI-Powered Automated Incident Response Systems. (2023). International Journal of Advanced Engineering Technologies and Innovations, 1(02): 282-304.

[8] Maddireddy, B.R. and B.R. Maddireddy, Evolutionary Algorithms in AI-Driven Cybersecurity Solutions for Adaptive Threat Mitigation. (2021). International Journal of Advanced Engineering Technologies and Innovations, 1(2): 17-43.

[9] Maddireddy, B.R. and B.R. Maddireddy, Proactive Cyber Defense: Utilizing AI for Early Threat Detection and Risk Assessment. (2020). International Journal of Advanced Engineering Technologies and Innovations, 1(2): 64-83.

[10] Maddireddy, B.R. and B.R. Maddireddy, Real-Time Data Analytics with AI: Improving Security Event Monitoring and Management. (2022). Unique Endeavor in Business & Social Sciences, 1(2): 47-62.

[11] Gadde, H., Integrating AI with Graph Databases for Complex Relationship Analysis. (2019). International Journal of Advanced Engineering Technologies and Innovations, 1(2): 294-314.

[12] Gadde, H., Improving Data Reliability with AI-Based Fault Tolerance in Distributed Databases. (2020). International Journal of Advanced Engineering Technologies and Innovations, 1(2): 183-207.

[13] Gadde, H., AI-Enhanced Data Warehousing: Optimizing ETL Processes for Real-Time Analytics. (2020). Revista de Inteligencia Artificial en Medicina, 11(1): 300-327.

[14] Gadde, H., AI-Assisted Decision-Making in Database Normalization and Optimization. (2020). International Journal of Machine Learning Research in Cybersecurity and Artificial Intelligence, 11(1): 230-259.

[15] Gadde, H., AI-Powered Workload Balancing Algorithms for Distributed Database Systems. (2021). Revista de Inteligencia Artificial en Medicina, 12(1): 432-461.

[16] Gadde, H., AI-Driven Predictive Maintenance in Relational Database Systems. (2021). International Journal of Machine Learning Research in Cybersecurity and Artificial Intelligence, 12(1): 386-409.

[17] Gadde, H., Secure Data Migration in Multi-Cloud Systems Using AI and Blockchain. (2021). International Journal of Advanced Engineering Technologies and Innovations, 1(2): 128-156.

[18] Gadde, H., Federated Learning with AI-Enabled Databases for Privacy-Preserving Analytics. (2022). International Journal of Advanced Engineering Technologies and Innovations, 1(3): 220-248.

[19] Gadde, H., Integrating AI into SQL Query Processing: Challenges and Opportunities. (2022). International Journal of Advanced Engineering Technologies and Innovations, 1(3): 194-219.

[20] Gadde, H., AI-Enhanced Adaptive Resource Allocation in Cloud-Native Databases. (2022). Revista de Inteligencia Artificial en Medicina, 13(1): 443-470.

[21] Goriparthi, R.G., Neural Network-Based Predictive Models for Climate Change Impact Assessment. (2020). International Journal of Machine Learning Research in Cybersecurity and Artificial Intelligence, 11(1): 421-421.

[22] Goriparthi, R.G., AI-Driven Automation of Software Testing and Debugging in Agile Development. (2020). Revista de Inteligencia Artificial en Medicina, 11(1): 402-421.

[23] Goriparthi, R.G., Scalable AI Systems for Real-Time Traffic Prediction and Urban Mobility Management. (2021). International Journal of Advanced Engineering Technologies and Innovations, 1(2): 255-278.

[24] Goriparthi, R.G., AI and Machine Learning Approaches to Autonomous Vehicle Route Optimization. (2021). International Journal of Machine Learning Research in Cybersecurity and Artificial Intelligence, 12(1): 455-479.

[25] Goriparthi, R.G., AI-Driven Natural Language Processing for Multilingual Text Summarization and Translation. (2021). Revista de Inteligencia Artificial en Medicina, 12(1): 513-535.

[26] Goriparthi, R.G., AI-Powered Decision Support Systems for Precision Agriculture: A Machine Learning Perspective. (2022). International Journal of Advanced Engineering Technologies and Innovations, 1(3): 345-365.

[27] Goriparthi, R.G., AI in Smart Grid Systems: Enhancing Demand Response through Machine Learning. (2022). International Journal of Machine Learning Research in Cybersecurity and Artificial Intelligence, 13(1): 528-549.

[28] Goriparthi, R.G., Deep Reinforcement Learning for Autonomous Robotic Navigation in Unstructured

Environments. (2022). International Journal of Advanced Engineering Technologies and Innovations, 1(3): 328-344.
[29] Goriparthi, R.G., Interpretable Machine Learning Models for Healthcare Diagnostics: Addressing the Black-Box Problem. (2022). Revista de Inteligencia Artificial en Medicina, 13(1): 508-534.
[30] Goriparthi, R.G., Leveraging AI for Energy Efficiency in Cloud and Edge Computing Infrastructures. (2023). International Journal of Advanced Engineering Technologies and Innovations, 1(01): 494-517.
[31] Chirra, D.R., AI-Based Real-Time Security Monitoring for Cloud-Native Applications in Hybrid Cloud Environments. (2020). Revista de Inteligencia Artificial en Medicina, 11(1): 382-402.
[32] Chirra, D.R., AI-Driven Risk Management in Cybersecurity: A Predictive Analytics Approach to Threat Mitigation. (2022). International Journal of Machine Learning Research in Cybersecurity and Artificial Intelligence, 13(1): 505-527.
[33] Chirra, D.R., AI-Enabled Cybersecurity Solutions for Protecting Smart Cities Against Emerging Threats. (2021). International Journal of Advanced Engineering Technologies and Innovations, 1(2): 237-254.
[34] Chirra, D.R., AI-Powered Adaptive Authentication Mechanisms for Securing Financial Services Against Cyber Attacks. (2022). International Journal of Advanced Engineering Technologies and Innovations, 1(3): 303-326.
[35] Chirra, D.R., Collaborative AI and Blockchain Models for Enhancing Data Privacy in IoMT Networks. (2022). International Journal of Machine Learning Research in Cybersecurity and Artificial Intelligence, 13(1): 482-504.
[36] Chirra, D.R., The Impact of AI on Cyber Defense Systems: A Study of Enhanced Detection and Response in Critical Infrastructure. (2021). International Journal of Advanced Engineering Technologies and Innovations, 1(2): 221-236.
[37] Chirra, D.R., Mitigating Ransomware in Healthcare: A Cybersecurity Framework for Critical Data Protection. (2021). Revista de Inteligencia Artificial en Medicina, 12(1): 495-513.
[38] Chirra, D.R., Next-Generation IDS: AI-Driven Intrusion Detection for Securing 5G Network Architectures. (2020). International Journal of Advanced Engineering Technologies and Innovations, 1(2): 230-245.
[39] Chirra, D.R., Secure Edge Computing for IoT Systems: AI-Powered Strategies for Data Integrity and Privacy. (2022). Revista de Inteligencia Artificial en Medicina, 13(1): 485-507.
[40] Chirra, D.R., Securing Autonomous Vehicle Networks: AI-Driven Intrusion Detection and Prevention Mechanisms. (2021). International Journal of Machine Learning Research in Cybersecurity and Artificial Intelligence, 12(1): 434-454.
[41] Syed, F.M. and F.K. ES, SOX Compliance in Healthcare: A Focus on Identity Governance and Access Control. (2019). Revista de Inteligencia Artificial en Medicina, 10(1): 229-252.
[42] Syed, F.M. and F.K. ES, Role of IAM in Data Loss Prevention (DLP) Strategies for Pharmaceutical Security Operations. (2021). Revista de Inteligencia Artificial en Medicina, 12(1): 407-431.
[43] Syed, F.M. and F.K. ES, The Role of AI in Enhancing Cybersecurity for GxP Data Integrity. (2022). Revista de Inteligencia Artificial en Medicina, 13(1): 393-420.
[44] Syed, F.M. and F.K. ES, Leveraging AI for HIPAA-Compliant Cloud Security in Healthcare. (2023). Revista de Inteligencia Artificial en Medicina, 14(1): 461-484.
[45] Syed, F.M. and E. Faiza Kousar, IAM for Cyber Resilience: Protecting Healthcare Data from Advanced Persistent Threats. (2020). International Journal of Advanced Engineering Technologies and Innovations, 1(2): 153-183.
[46] Syed, F.M. and F.K. ES, IAM and Privileged Access Management (PAM) in Healthcare Security Operations. (2020). Revista de Inteligencia Artificial en Medicina, 11(1): 257-278.
[47] Syed, F.M. and F. ES, Automating SOX Compliance with AI in Pharmaceutical Companies. (2022). International Journal of Machine Learning Research in Cybersecurity and Artificial Intelligence, 13(1): 383-412.
[48] Syed, F.M., F.K. ES, and E. Johnson, AI-Driven Threat Intelligence in Healthcare Cybersecurity. (2023). Revista de Inteligencia Artificial en Medicina, 14(1): 431-459.
[49] Syed, F.M. and F. ES, AI-Driven Identity Access Management for GxP Compliance. (2021). International Journal of Machine Learning Research in Cybersecurity and Artificial Intelligence, 12(1): 341-365.
[50] Syed, F.M., F. ES, and E. Johnson, AI and the Future of IAM in Healthcare Organizations. (2022). International Journal of Advanced Engineering Technologies and Innovations, 1(2): 363-392.
[51] Chirra, B.R., Advanced Encryption Techniques for Enhancing Security in Smart Grid Communication Systems. (2020). International Journal of Advanced Engineering Technologies and Innovations, 1(2): 208-229.
[52] Chirra, B.R., AI-Driven Fraud Detection: Safeguarding Financial Data in Real-Time. (2020). Revista de Inteligencia Artificial en Medicina, 11(1): 328-347.
[53] Chirra, B.R., AI-Driven Security Audits: Enhancing Continuous Compliance through Machine Learning. (2021). International Journal of Machine Learning Research in Cybersecurity and Artificial Intelligence, 12(1): 410-433.
[54] Chirra, B.R., Enhancing Cyber Incident Investigations with AI-Driven Forensic Tools. (2021). International Journal of Advanced Engineering Technologies and Innovations, 1(2): 157-177.
[55] Chirra, B.R., Intelligent Phishing Mitigation: Leveraging AI for Enhanced Email Security in Corporate Environments. (2021). International Journal of Advanced Engineering Technologies and Innovations, 1(2): 178-200.
[56] Chirra, B.R., Leveraging Blockchain for Secure Digital Identity Management: Mitigating Cybersecurity

Vulnerabilities. (2021). Revista de Inteligencia Artificial en Medicina, 12(1): 462-482.
[57] Chirra, B.R., Ensuring GDPR Compliance with AI: Best Practices for Strengthening Information Security. (2022). International Journal of Machine Learning Research in Cybersecurity and Artificial Intelligence, 13(1): 441-462.
[58] Chirra, B.R., Dynamic Cryptographic Solutions for Enhancing Security in 5G Networks. (2022). International Journal of Advanced Engineering Technologies and Innovations, 1(3): 249-272.
[59] Chirra, B.R., Strengthening Cybersecurity with Behavioral Biometrics: Advanced Authentication Techniques. (2022). International Journal of Advanced Engineering Technologies and Innovations, 1(3): 273-294.
[60] Chirra, B.R., AI-Driven Vulnerability Assessment and Mitigation Strategies for CyberPhysical Systems. (2022). Revista de Inteligencia Artificial en Medicina, 13(1): 471-493.
[61] Nalla, L.N. and V.M. Reddy, SQL vs. NoSQL: Choosing the Right Database for Your Ecommerce Platform. (2022). International Journal of Advanced Engineering Technologies and Innovations, 1(2): 54-69.
[62] Nalla, L.N. and V.M. Reddy, Scalable Data Storage Solutions for High-Volume E-commerce Transactions. (2021). International Journal of Advanced Engineering Technologies and Innovations, 1(4): 1-16.
[63] Reddy, V.M. and L.N. Nalla, The Impact of Big Data on Supply Chain Optimization in Ecommerce. (2020). International Journal of Advanced Engineering Technologies and Innovations, 1(2): 1-20.
[64] Reddy, V.M. and L.N. Nalla, Harnessing Big Data for Personalization in E-commerce Marketing Strategies. (2021). Revista Espanola de Documentacion Cientifica, 15(4): 108-125.
[65] Reddy, V.M. and L.N. Nalla, The Future of E-commerce: How Big Data and AI are Shaping the Industry. (2023). International Journal of Advanced Engineering Technologies and Innovations, 1(03): 264-281.
[66] Reddy, V.M. and L.N. Nalla, Enhancing Search Functionality in E-commerce with Elasticsearch and Big Data. (2022). International Journal of Advanced Engineering Technologies and Innovations, 1(2): 37-53.
[67] Reddy, V.M., Data Privacy and Security in E-commerce: Modern Database Solutions. (2023). International Journal of Advanced Engineering Technologies and Innovations, 1(03): 248-263.
[68] Nalla, L.N. and V.M. Reddy, Comparative Analysis of Modern Database Technologies in Ecommerce Applications. (2020). International Journal of Advanced Engineering Technologies and Innovations, 1(2): 21-39.
[69] Reddy, V.M., Blockchain Technology in E-commerce: A New Paradigm for Data Integrity and Security. (2021). Revista Espanola de Documentacion Cientifica, 15(4): 88-107.
[70] Nalla, L.N. and V.M. Reddy, AI-Driven Big Data Analytics for Enhanced Customer Journeys: A New Paradigm in E-Commerce. International Journal of Advanced Engineering Technologies and Innovations, 1: 719-740.
[71] Damaraju, A., Social Media as a Cyber Threat Vector: Trends and Preventive Measures. (2020). Revista Espanola de Documentacion Cientifica, 14(1): 95-112.
[72] Damaraju, A., Data Privacy Regulations and Their Impact on Global Businesses. (2021). Pakistan Journal of Linguistics, 2(01): 47-56.
[73] Damaraju, A., Mobile Cybersecurity Threats and Countermeasures: A Modern Approach. (2021). International Journal of Advanced Engineering Technologies and Innovations, 1(3): 17-34.
[74] Damaraju, A., Securing Critical Infrastructure: Advanced Strategies for Resilience and Threat Mitigation in the Digital Age. (2021). Revista de Inteligencia Artificial en Medicina, 12(1): 76-111.
[75] Damaraju, A., Insider Threat Management: Tools and Techniques for Modern Enterprises. (2021). Revista Espanola de Documentacion Cientifica, 15(4): 165-195.
[76] Damaraju, A., Adaptive Threat Intelligence: Enhancing Information Security Through Predictive Analytics and Real-Time Response Mechanisms. (2022). International Journal of Advanced Engineering Technologies and Innovations, 1(3): 82-120.
[77] Damaraju, A., Integrating Zero Trust with Cloud Security: A Comprehensive Approach. (2022). Journal Environmental Sciences And Technology, 1(1): 279-291.
[78] Damaraju, A., Securing the Internet of Things: Strategies for a Connected World. (2022). International Journal of Advanced Engineering Technologies and Innovations, 1(2): 29-49.
[79] Damaraju, A., Social Media Cybersecurity: Protecting Personal and Business Information. (2022). International Journal of Advanced Engineering Technologies and Innovations, 1(2): 50-69.
[80] Damaraju, A., The Role of AI in Detecting and Responding to Phishing Attacks. (2022). Revista Espanola de Documentacion Cientifica, 16(4): 146-179.
[81] Suryadevara, S. and A.K.Y. Yanamala, Fundamentals of Artificial Neural Networks: Applications in Neuroscientific Research. (2020). Revista de Inteligencia Artificial en Medicina, 11(1): 38-54.
[82] Suryadevara, S. and A.K.Y. Yanamala, Patient apprehensions about the use of artificial intelligence in healthcare. (2020). International Journal of Machine Learning Research in Cybersecurity and Artificial Intelligence, 11(1): 30-48.
[83] Woldaregay, A.Z., B. Yang, and E.A. Snekkenes. Data-Driven and Artificial Intelligence (AI) Approach for Modelling and Analyzing Healthcare Security Practice: A Systematic. (2020). in Intelligent Systems and Applications: Proceedings of the 2020 Intelligent Systems Conference (IntelliSys) Volume 1. Springer Nature.
[84] Suryadevara, S. and A.K.Y. Yanamala, A Comprehensive Overview of Artificial Neural Networks: Evolution, Architectures, and Applications. (2021). Revista de Inteligencia Artificial en Medicina, 12(1): 51-76.
[85] Suryadevara, S., A.K.Y. Yanamala, and V.D.R. Kalli, Enhancing Resource-Efficiency and Reliability in Long-Term Wireless Monitoring of Photoplethysmographic Signals. (2021). International Journal of Machine

Learning Research in Cybersecurity and Artificial Intelligence, 12(1): 98-121.

[86] Yanamala, A.K.Y. and S. Suryadevara, Adaptive Middleware Framework for Context-Aware Pervasive Computing Environments. (2022). International Journal of Machine Learning Research in Cybersecurity and Artificial Intelligence, 13(1): 35-57.

[87] Yanamala, A.K.Y. and S. Suryadevara, Cost-Sensitive Deep Learning for Predicting Hospital Readmission: Enhancing Patient Care and Resource Allocation. (2022). International Journal of Advanced Engineering Technologies and Innovations, 1(3): 56-81.

[88] Yanamala, A.K.Y., Secure and private AI: Implementing advanced data protection techniques in machine learning models. (2023). International Journal of Machine Learning Research in Cybersecurity and Artificial Intelligence, 14(1): 105-132.

[89] Yanamala, A.K.Y. and S. Suryadevara, Advances in Data Protection and Artificial Intelligence: Trends and Challenges. (2023). International Journal of Advanced Engineering Technologies and Innovations, 1(01): 294-319.

[90] Yanamala, A.K.Y., S. Suryadevara, and V.D.R. Kalli, Evaluating the impact of data protection regulations on AI development and deployment. (2023). International Journal of Advanced Engineering Technologies and Innovations, 1(01): 319-353.