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SURVEY OF THE DEVELOPMENT PROCESSES AND EVOLUTION OF THE INTERNATIONAL CLASSIFICATION OF DISEASES

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Abstract. The International Classification of Diseases (ICDs) has a global application in epidemiological research, health administration, and diagnostic studies; The ICDs are a classification system within the healthcare system, Developed and endorsed by the World Health Organization (WHO) to provide a comprehensive range of diagnostic codes for categorizing diseases. It encompasses exhaustive classifications of diverse indications, manifestations, abnormal findings, grievances, societal circumstances, and extrinsic factors contributing to injury or illness. This system relied entirely on clinical data sets collected by officials, based on which the ICDs are coded for many purposes, such as billing systems, determining the type of disease, and the types of treatments used. Recently, electronic health record systems appeared to be adopted in writing clinical notes, leading researchers to integrate modern technology in Natural Language Processing, Machine Learning and Deep Learning techniques to code the ICDs more effectively and accurately. The factors mentioned helped shed more light on the importance of this system, its objectives, and the developments that have been made since its inception. Also, they led us in this paper to conduct a comprehensive survey on the latest technologies prepared by researchers in the classification and coding of diseases and the processes that have been adopted in this regard.

1. INTRODUCTION

There are numerous uses for the International Classification of Diseases (ICDs) worldwide [45]. The frequency, causes, and consequences of human illness and death must be addressed in detail [12]. This is accomplished through ICDs data coding and systematic reporting [34]. In primary, secondary, and

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tertiary healthcare settings, as well as on official death certificates, the foundation for health recording and statistical analysis of illnesses is a clinical language encoded with the ICDs [28, 64].

The information mentioned above and the data are helpful for payment systems, service planning, quality management, safety management, and research on health services [26]. Additionally, using the ICDs to categorize diagnostic advice creates consistency in data collection and facilitates in-depth research [14, 29]. For the past 150 years, the ICD has served as the primary framework for facilitating comparing data on morbidity and mortality rates across different geographic regions and periods. ICD-11 is the most recent edition of the ICD, first published in the 1800s [13]. In 2019, at its 72nd meeting, the World Health Assembly officially endorsed this version. The new regulation is scheduled to take effect on January 1, 2022 [27].

The study also addresses one of the most critical developmental aspects in the international classification of diseases based on Electronic Health Records (EHRs). It explores how to benefit from their development. This leads us to the last two sections of this research, which shed light on how to benefit from NLP techniques used in the processing and classifying of ICDs techniques based on the data from EHRs. These records have recently encountered numerous problems, which are discussed in the tenth and eleventh sections. The research focuses on surveying some of the latest studies published in the last five years, demonstrating a complete reliance on Natural Language Processing (NLP) techniques and the latest Machine Learning and Deep Learning techniques for disease classification and coding in the ICD.

This study aims to define the concept of ICDs, highlight its importance, explore its evolutionary stages and examine the data used by previous researchers. The article is structured as follows: Section 1 provides an introduction outlining the importance of ICDs in healthcare systems and the study's objectives. Following the introduction, Section 2 offers a comprehensive summary of the evolution of ICDs, highlighting key milestones and changes over time. Section 3 focuses on the significance of ICD-10 and its applications in disease classification and health analysis. Section 4 explores the critical role of accurate ICD coding in enhancing billing, research, and public health initiatives. Moving forward, Section 5 investigates the datasets utilized in ICD-based disease classification and health analysis. In Section 6, recent studies concerning ICD-10 within the context of COVID-19 are reviewed, presenting valuable insights into its application during pandemic scenarios. Section 7 discusses the seamless transition to ICD systems and the utilization of various applications to facilitate this process. Section 8 delves into the impact of EHRs on healthcare and research focusing focus on leveraging ICD codes within EHR systems. The subsequent section, Section 9, explores the integration of NLP techniques with ICD codes in healthcare, showcasing the potential benefits and challenges. Section 10 explores the burgeoning field of AI and Deep Learning and its role in enhancing disease coding within the ICD system. Section 11 examines advancements in disease classification based on ICD codes using Machine Learning techniques, highlighting recent developments in the field. Building on this, Section 12 discusses cutting-edge AI techniques, including NLP and Deep Learning, for disease classification using ICD codes and EHRs. Lastly, 13 concludes the article, summarizing key findings and insights, emphasizing the importance of ICDs in healthcare, and outlining future directions and potential areas for further research.

2. SUMMARY AND EVOLUTION OF THE ICDS

The ICD has undergone development across several stages, ranging from the 9th edition to the 11th edition. Table 1 below provides a concise summary of the different types of ICDs. The ICD has evolved through various stages, ranging from the 9th edition to the 11th edition [41]. The table serves as a valuable reference for readers, giving them a quick overview of the three ICD versions, their characteristics, and their advantages in various healthcare contexts. The table also highlights the benefits associated with each type, from standardized disease classification and data analysis to resource allocation and improved user-friendliness. This summary serves as a valuable reference to understand the features and advantages of each ICD version.

TABLE 1. Summary of ICD types and their benefits

Reference	ICD Type	Description and Benefits
[51]	ICD-9	**Appearance:** The ICD ninth revision (ICD-9) was first published in 1979 and has undergone successive revisions. The most recent version, The ICD-9-CM Version 2013, was publicly available in 2012. **Domain:** The ICD-9-CM is widely used by various healthcare institutions, including hospitals, clinics and private practices of doctors. In addition, academic research institutions, government agencies and insurance companies also use this classification system. **Benefits:** 1. It provides a standardized method for classifying diseases and injuries. 2. It facilitates the collection and analysis of data on diseases and injuries. 3. It aids in tracking the prevalence of diseases. 4. It assists in the allocation of funds for prevention and treatment. 5. Healthcare organizations and government agencies utilize it.
[8]	ICD-10	**Appearance:** The ICD tenth revision (ICD-10) manual was first introduced in 1992 and has since undergone iterations of modification. The most recent iteration of the ICD, was made available to the public in 2021, superseding all previous versions. **Domain:** The ICD-10 is used by diverse healthcare establishments, including hospitals, outpatient clinics, and physician's offices. Furthermore, this tool is employed by academic research institutions, governmental entities, and insurance companies. **Benefits:** 1. Various healthcare organizations and government agencies utilize it. 2. It assists in allocating resources for prevention and treatment. 3. It aids in tracking the burden of disease. 4. It enables the collection and analysis of data on diseases and injuries. 5. It offers a standardized approach to classify diseases and injuries.
[25]	ICD-11	**Appearance:** The ICD eleventh revision (ICD-11) is being implemented in stages, with the first stage being completed in 2022. By 2027, all countries are expected to be using ICD-11. **Domain:** The ICD-11 is a more comprehensive and flexible system than ICD-10. It includes new codes for emerging diseases, such as Zika and Ebola, and has been updated to reflect the latest medical knowledge. ICD-11 is also more user-friendly, with a more straightforward coding structure and intuitive search engine. **Benefits:** 1. It provides a comprehensive and accurate method for classifying diseases and injuries. 2. It is more user-friendly compared to ICD-10. 3. Its staged implementation makes it easier for countries to transition to the new system.

3. ICD-10: SIGNIFICANCE AND APPLICATIONS IN DISEASE CLASSIFICATION AND HEALTH ANALYSIS

ICD-10, short for International Classification of Diseases and related health problems, is a diagnostic coding system used by clinicians and researchers to describe various diseases and injuries. The World

Health Organization (WHO) developed this classification system, known as ICD-10. The application of this technology may currently be seen in more than 190 nations across the world [18]. The ICD-10 comprises three volumes: a tabular list of diseases and injuries, an index, and guidelines for selecting and modifying codes [24]. The arrangement of the tabular listing is based on categorizing bodily systems and corresponding afflictions or traumas [31].

The index is a comprehensive compilation of diseases and injuries arranged alphabetically, accompanied by corresponding code numbers [9]. The guidelines about the selection and modification of codes are implemented to ensure their appropriate usage. The ICD-10 is used by various entities, including governmental bodies, healthcare professionals, researchers, and insurance companies, to gather and scrutinize information about illnesses and physical harm [47]. Furthermore, it monitors the ailment's prevalence and distributes resources for its prevention and management [22]. Various sources [52] state that the ICD-10 is crucial in public health and healthcare. Adopting a uniform classification system for illnesses and physical harm streamlines the methodical gathering and evaluation of information about said afflictions. The data can aid in monitoring disease burden, improving the allocation of resources for prevention and treatment, and augmenting public health outcomes [36].

4. ICD CODING: ENHANCING ACCURACY FOR BILLING, RESEARCH, AND PUBLIC HEALTH

An ICD method is a process of assigning a code to a diagnosis [42]. Among all the different ICD systems, the ICD-10-CM method is the most frequently utilized. The approach taken by ICD-10-CM can be broken down into three stages:

- **Identify the diagnosis [5]**: The first step is to identify the diagnosis. This can be done by examining the patient's medical history, physical examination, and laboratory results.
- **Find the code [50]**: Once the diagnosis has been identified, the next step is to find the corresponding code in the ICD-10-CM manual. The manual is divided into chapters, each covering a different body system. Within each chapter, the codes are organized based on the severity of the condition.
- **Assign the code [48]**: The final step is to assign the code to the diagnosis. Once again, the code should be written in the correct format and remain consistent with the patient's medical record.

The ICD-10-CM method is complex, but it is crucial to ensure accurate coding of diagnoses. Accurate coding is essential for various reasons, including:

A. Billing [61]: Accurate coding is essential for precise billing. Healthcare providers must be able to accurately bill for their services to be reimbursed by insurance companies.

B. Research [23]: Accurate coding is vital for research. Researchers need to accurately identify patients with specific conditions to study those conditions.

C. Public health [30]: Accurate coding is crucial for public health. Public health officials need to accurately track the incidence and prevention of diseases to develop effective prevention and treatment strategies.

5. DATASETS IN ICDS FOR DISEASE CLASSIFICATION AND HEALTH ANALYSIS

There are numerous datasets utilized in the ICDs. The table below presents the most commonly used datasets by healthcare providers, researchers, and public health officials for classifying diseases, injuries, and other health conditions. Furthermore, this data is employed to monitor disease incidence and prevalence, devise effective prevention and treatment strategies, and enhance healthcare and public health outcomes [58]. Table 2 provides a summary of the datasets within ICDs as a whole.

TABLE 2. Summary of Datasets in ICDs: Compilation of Various Data Sources and Their Descriptions for Disease Classification and Health Analysis

Reference	Name	Description
[53]	ICD-10-CM	This data collection comprises the whole ICD-10-CM manual, including all the codes and their descriptions.
[55]	ICD-10-PCS	This dataset contains the full text of the ICD-10-PCS manual, including all codes and their definitions.
[20]	ICD-11	This dataset contains the full text of the ICD-11 manual, including all the codes and their definitions.
[40]	ICD-O-3	This dataset contains the full text of the ICD-O-3 manual, including all codes and their definitions.
[62]	ICD-10-CM-CMOP	This data file includes the ICD-10-CM-CMOP manual, each code, and its corresponding explanation.
[1]	Clinical decision support	This uses data to help clinicians make better decisions about patient care.
[3]	Public health surveillance	This uses data to track the incidence and prevalence of diseases and to identify trends.
[57]	Healthcare policy analysis	This uses data to analyze the effectiveness of healthcare policies and programs.
[6]	Healthcare quality improvement	This uses data to identify and improve areas of healthcare that need improvement.

Table 2 presents comprehensive datasets summarizing various datasets in the ICD system. These datasets play an essential role in disease classification and health analysis. The table includes references, dataset names and detailed descriptions of each dataset. These datasets serve diverse purposes: clinical decision support, public health surveillance, health policy analysis, and healthcare quality improvement. Researchers, healthcare providers, and public health authorities heavily depend on these datasets to efficiently monitor disease incidence, devise effective prevention strategies, and make well-informed decisions concerning patient care.

6. RECENT STUDIES ON ICD-10 IN THE CONTEXT OF COVID-19

The preceding studies have addressed the topic of ICD-10, and Table 3 presents a compilation of recent studies within the domain of Covid-19 that have explored this subject. Table 3 summarises previous studies on ICD-10 topics in the context of COVID-19. The table includes references, publication years, authors, ICD types and contributions of each study. These studies explore various aspects of ICD-10 codes concerning COVID-19, such as their predictive value, accuracy and use in analyzing reported deaths and patient diagnoses. In addition, one study examines the validation and use of specific ICD-10 codes for ”Post COVID-19 status, Unspecified”. Overall, the table provides an overview of research efforts in this area.

TABLE 3. Summary of Previous Studies on ICD-10 Topics in the Context of COVID-19

Reference	Year	Authors	ICD Types	Contribution
[44]	2021	K. Lynch et al.	ICD-10 U07.1	Positive predictive value (PPV) of the ICD-10 code U07.1, which refers to the COVID-19 virus that was discovered in the Department of Veterans Affairs (VA) using the Corporate Data Warehouse (CDW) of the Veterans Administration.
[32]	2021	A. Gundlapalli et al.	ICD-10 U07.1	The research aims to analyze the ICD using ICD-10; a diagnosis on official death certificates is an appropriate and effective way to establish whether reported deaths from COVID-19 have been overestimated.
[7]	2021	J. Hirsch et al.	ICD-10 U07.1	In April 1 - July 31, 2020, list all Mass General Brigham Health System inpatient encounters with SARS-CoV-2 RT-PCR. COVID-19 positive patients with ICD-10 U07.1 coding agreement. Report sensitivity, specificity, PPV, and NPV of ICD-10 U07.1 across subgroups. Multivariate logistic regression used to find determinants of COVID-19 susceptibility in infected patients. STATA (College Station, TX) analyzed data.
[10]	2021	J. Boilen et al.	ICD-10 U07.1	Examine the positive predictive value (PPV) of the diagnosis codes for Coronavirus disease 2019 (COVID-19) utilizing ICD-10.
[49]	2023	E. Pfaff et al.	ICD-10 U09.9	It took around two years for the United States to approve a code for the ICD-10-CM, and there is still debate regarding the clinical diagnosis and the underlying processes of prolonged COVID. The research of the heterogeneity of acceptance and usage of U09.9, the ICD-10-CM code for "Post COVID-19 condition, Unspecified," that was performed using the suggested approach made use of the biggest publicly accessible HIPAA-limited dataset of US COVID-19 patients.

7. Leveraging Applications for a Seamless ICD Transition

Mobile applications can be valuable tools to facilitate a seamless transition from ICD-9 to ICD-10. To accomplish this, there is a temporary need for "cross-walking" between the older ICD-9 code set and the newer ICD-10 code set to facilitate the migration of systems, applications, and data within the healthcare industry. This requirement is essential in the healthcare sector. Since there is not always a one-to-one code equivalent between the coding systems, this process can be achieved by following these steps [43]:

- **Insulating legacy systems**: In some cases, legacy systems must be temporarily insulated from the impact of the ICD-10 changes. In such situations, they must accept transactions with ICD-10 codes and then exchange them for ICD-9 codes that the system understands.
- **Locating the ICD-10 example files**: This topic identifies the directory location of the ICD-10 example files.
- **Using the ICD-10 example files**: This topic describes how to use the ICD-10 example files.

The following points describe examples of apps using ICD-10:

A. Mycobacterium Tuberculosis Complex (MTBC) ICD 9-10 [19]: To categorize ICD-10 codes according to respective specialties.

- **Define:** MTBC's innovative program for the ICD-10 transition facilitates the conversion of ICD-9 diagnostic codes to their corresponding ICD-10 versions, making it an outstanding tool for medical practices and clinicians. Time is saved using this helpful tool, as it contains all ICD-9 codes and their matching ICD-10 numbers. ICD-10 codes can be quickly searched using our ICD 9-10 converter, and searches can be saved to favorites. Access to the ICD-9 and associated ICD-10 codes most frequently used in your specialities can be gained with just one tap.
- **Pros and cons:** Feature an exceptional user interface and experience. It is straightforward to operate and very user-friendly. In addition to the incredibly user-friendly capability of browsing for codes based on specialists, the search tool is also of great assistance. Additionally, it gives you the option to favorite particular codes, allowing instant access with just a single click to the codes you will use most frequently.
- **Best choice:** To categorize ICD-10 codes according to respective specialties.

B. ICD-10 Consult 2016 Free [2]:

- **Define:** ICD10 Consult places the ICD10-CM resource that is the most searchable, comprehensive, and up-to-date at your disposal. This source is desired as an Electronic Medical Record (EMR) offering a versatile search that can be done in various languages, a profound grasp of the codes, quick translation from ICD-9 to ICD-10, and more.
- **Pros and cons:** ICD-10 Consult 2016 Free introduces its app through an excellent introductory process that teaches how to utilize it. This program may not be as aesthetically pleasing or complicated as others on this list; however, it makes up for that by having excellent search functionality.
- **Best choice:** The superior search functionalities and adaptability.

C. Quick ICD-10 [19]:

- **Define:** The Quick ICD-10 tool offers a rapid and uncomplicated approach to search for and convert ICD-9 codes to their corresponding ICD-10 codes and vice versa. It is possible to search codes either by numerical value or by description. Additionally, it allows users to save preferred codes for future utilization. Commonly utilized ICD-10 codes can be printed or transmitted via email. Efficient future conversions are facilitated by accessing a catalog of prior inquiries.
- **Pros and cons:** The portrayal of this application in the digital marketplace does not overstate its intricacy; it is indeed straightforward to operate. The software's primary interface allows converting from ICD-9 codes to their respective ICD-10 counterparts, as well as the reverse conversion from ICD-10 codes to their corresponding ICD-9 forms. Like MTBC ICD 9-10, this software enables users to designate specific codes as favorites and store them on their devices for convenient retrieval later.
- **Optimal selection:** Efficient and expeditious transformation of ICD-9 to ICD-10.

8. The Impact of EHRs on Healthcare and Research: Leveraging the ICD

With the widespread deployment of EHRs, there is a growing demand for the secondary use of EHR data in diverse health services and clinical research [11]. As a result, the transition from paper-based to EHRs are regarded as a significant scientific and technical revolution in healthcare technology. Previously, checking typos, grammatical mistakes, and other obvious errors, such as missed turn signals, solely rested with the individual recording medical information. However, the introduction of EHRs has led to an increase in the time physicians spend in front of computers, rising from 49% to 66%. Furthermore, over the past decade, there has been a notable surge in hospitals implementing EHRs with sophisticated features [33]. This advancement has prompted numerous healthcare and technology experts to recognize EHRs as a potentially invaluable data source for studies to advance our understanding of diseases and their classifications. The widespread adoption of the ICD has increased reliance on EHRs for automatic disease classification. Our research's current primary goal is to provide a broad overview of studies focusing on ICD using the latest approaches.

9. NLP in Healthcare: Integrating ICD Codes

NLP is a subfield of Computer Science and, more specifically, an offshoot of Artificial Intelligence (AI) that focuses on teaching computers to comprehend written and spoken language analogous to how humans do it. This can be accomplished in several different contexts, including translation and interpretation. Combining statistical, Machine Learning, and Deep Learning models produces NLP in the field of computational linguistics [39]. When these technologies are combined, computers can evaluate human language in text or speech data and 'understand' the meaning of what is said or written. This understanding includes the purpose and feelings of the person speaking or writing the words. Computer programmers specialising in NLP can translate text from one language to another, respond verbally to inquiries, and immediately summarize enormous amounts of information—even in real time. Most certainly, people have interacted with NLP through voice-controlled GPS systems, speech-to-text dictation software, customer service chatbots, digital assistants, and other consumer conveniences [60]. NLP is becoming an increasingly crucial component of enterprise solutions that simplify mission-critical business procedures, increase staff productivity, and expedite business operations.

Several NLP jobs are responsible for parsing human text and voice input in such a way as to assist the computer in making sense of the information it is taking in. In recent years, one of the most significant applications of NLP has been encoding the ICD. The addition of ICD codes might enhance many NLP-related tasks. As a result of developments in technology, ICD codes may be used for an even wider variety of functions in the years to come [21]. NLP has many applications in the field of ICD codes (see Figure 1).

10. Leveraging AI and Deep Learning for Enhanced Disease Coding within the ICDs System

As mentioned in previous sections, the ICD code is widely used as a reference in medical systems and for billing purposes. However, the classification of illnesses into the ICD codes still heavily relies on

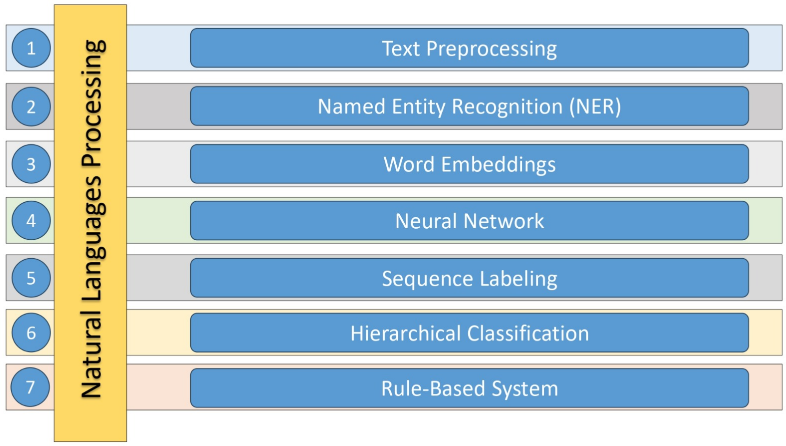

FIGURE 1. Applications of NLP in ICDs

humans reading substantial amounts of textual material, making the coding process both time-consuming and challenging. The transition from ICD-9 to ICD-10 has further complicated the coding process [16]. Moreover, several additional issues impede the clinical decision process, as outlined below [38].

First: Medical jargon idiosyncrasies Free-text clinical notes frequently contain unusual terms, awkward constructions, and unclear abbreviations. Spelling and grammatical mistakes are common in free-text clinical notes because their authors generally write them quickly [15]. Additionally, negating phrases are positioned far from the negated notion, and equivalents for clinical ideas are used interchangeably [38].

Second: The lack of EHRs The lack of EHRs has long been an obstacle to automated coding since many hospitals still keep records on paper, limiting the quantity of training data accessible. In poor nations, where structured EHRs are not widely used, practitioners must rely on unstructured clinical notes for decision-making. When data is translated into organized EHRs, sometimes vital patient information is lost [35].

Third: Lack of labels for rare diseases Even though many disease ontologies contain hundreds of labels, there aren't any labels for rare diseases. In order to improve the accuracy of their algorithm, several studies have eliminated the least common diseases from their training set and instead focused on the k most common diseases (or labels) [15]. However, in actual healthcare settings, where many uncommon diseases have catastrophic consequences when ignored, such carelessness would not be tolerated.

Fourth: Insufficient training data A substantial amount of training data is needed; patient medical records are seldom available in open-access medical archives. Since Machine Learning models gain expertise through practice, extensive training data is required for excellent performance [56].

In order to help disease coders, Deep Learning- and NLP-related techniques have been investigated. The fast use of EMRs has created a vast quantity of clinical data that may be used to predict ICD codes using ML models [46]. These reasons make the ICD operation a perfect environment for fast merging with AI. The objectives of using Machine Learning and Deep Learning with ICDs are as follows:

- Intended to automatically identify the appropriate diagnostic and treatment codes [16].
- Predict ICD-10 codes accurately, which might aid healthcare professionals in improving their clinical judgment and quality of care [63].
- Try to reduce the burden of manual coding and programming operations [17].
- Reduce expenses, time-consuming, and error-prone tasks [38].

Figure 2 demonstrates the application of Machine Learning and Deep Learning for ICD-based AI, a promising approach to enhance the efficiency of disease coding within the context of the ICD system.

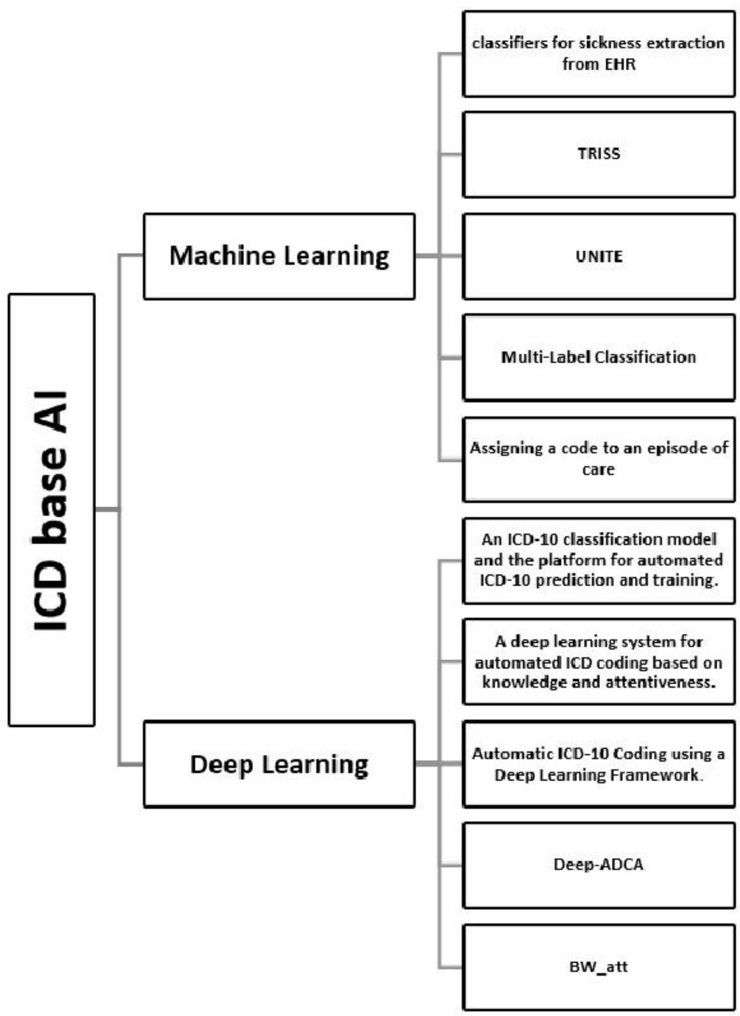

FIGURE 2. Machine Learning and Deep Learning for ICD-based AI

11. Advancements in ICD-based Disease Classification using Machine Learning

This section focuses on literary works that have employed Machine Learning techniques, integrating ICD techniques with EHRs to build an intelligent disease classifier. The main objective is to achieve high-performance accuracy and avoid traditional errors from manual classifications and human programming. We have selected five published studies that used NLP techniques and Machine Learning based on ICD information for the review. These studies have been highlighted based on three main components: Approach, Objective, and Result.

Jingqing Zhang et al.'s work on creating Machine Learning classifiers for sickness extraction from EHR: Clinician-in-the-Loop enables people to rate Machine Learning classifiers based on their understanding of clinical factors and diagnostic labels. The machine-learning-based method outperforms the ICD-code baseline by identifying many more cases.

This research demonstrates the utility of obtaining phenotypic information from unstructured text. Structured clinical characteristics alone are poor classifiers due to missing and erroneous values. Phenotype extraction from the clinical language in EHRs helps understand high-impact traits and improves classification accuracy. This research proposes a disease-neutral, large-scale technique for various illnesses. With the Clinician in the Loop and AutoML framework, models can be rapidly configured without the need for clinicians or engineers [65].

Machine Learning models outperform TRISS for the Trauma and Injury Severity Score (TRISS): Predicting fatalities after trauma has gained attention for its potential usefulness in areas like quality assurance and benchmarking. Zachary Tran et al. explored using ML-based models, which use powerful mathematical approaches and consider non-linear connections among factors.

This study employed an ML algorithm to predict survival based on patient demographics, vital signs, and previously validated ICD-10-CM injury characteristics. XGBoost outperformed TRISS in terms of classification and calibration. Its efficacy was consistent across all the in-hospital outcomes studied, although its balanced accuracy was subpar. The outstanding performance of the full XGBoost model further substantiates its potential use as a mortality prediction model. Lastly, several patient characteristics and injury characteristics were identified that are linked to long-term survival, requiring further analysis [59].

Unsupervised knowledge integration (UNITE): Yuri Ahuja and others suggested a novel UNITE for the speedy and accurate assignment of ICD codes from clinical notes. This method does not rely on any ICD data collected in the past for training purposes.

UNITE has extraordinary mobility among several EMR systems. The method discussed has the potential to significantly lessen the reliance on human involvement in ICD coding, thus promoting patient safety by reducing the incidence of medical coding errors and making the repercussions of such errors simpler to comprehend. Lastly, UNITE can increase the precision of clinical phenotyping by rating each comment on how helpful it is concerning a specific health condition [54].

Multi-Label Classification: In EHRs, applying various labels to a patient's file is common practice, choosing from a vast pool of options. One such activity is assigning diagnostic codes, which can be daunting due to the sheer number of possible descriptors (14,000 ICD-9 codes and 68,000 ICD-10 codes).

Classification across a large label set can be recast as a multi-label assignment for large-scale multiple phenotyping, identification of an issue list, or an essential patient representation. Tal Baumel et al. explored a unique use of neural architectures to extract helpful information from the EHR's unstructured patient notes. They looked at four cutting-edge models, using the MIMIC datasets, for the challenging task of multi-label classification [4].

Assigning a code to an episode of care: The foundation of this work, as mentioned by Rajvir KAUR and others, rests on four pillars: Re-cleaned clinical records to extract data on primary and secondary diagnoses, diabetic conditions, smoking-related diagnoses, additional conditions, primary and secondary procedures, anaesthetic type, ventilation information, and allied healthcare interventions.

Information from the National Center for Classification in Health (NCCH) was used to obtain this data. After removing irrelevant data from the healthcare records, the next step was to convert the textual information into numerical form for feature extraction. Then, seven different classifiers - Support Vector Machine (SVM), Naive Bayes (NB), Decision Tree (DT), Random Forest (RF), k-Nearest Neighbor (kNN), AdaBoost, and Multi-Layer Perceptron (MLP) - were compared against each other. Finally, an 80-20 ratio was employed in all the Machine Learning studies, indicating that 80% of the data was used for training and 20% for testing. Precision, Recall, Accuracy, F-score, and more were used as evaluation criteria [37].

In healthcare, the accurate and efficient classification of diseases plays a critical role in clinical practice, research, and decision-making processes. However, traditional disease classification methods, such as the ICD codes, have shown limitations in precision and brevity, leading to potential errors and high failure rates in some instances. To address these challenges, researchers have explored innovative approaches that combine NLP and Machine Learning techniques to enhance disease classification accuracy and automate the coding process.

Table 4 presents a comprehensive review of disease classification studies that have leveraged ICD codes, NLP, and Machine Learning approaches. The table summarizes the key findings from each study, including the reference, dataset used, the approach employed, the objective of the research, and the corresponding results.

TABLE 4. Review of Disease Classification Using ICDs, NLP, and Machine Learning

Reference	Dataset	Approach	Objective	Result
[65]	MIMIC-III	NLP for phenotyping and AutoML with Clinician in the Loop mechanism	Due to the lack of precision, brevity, and potential for error, ICD codes frequently fail to adequately classify individuals for certain diseases in actual clinical practice, leading to high failure rates and the loss of uncoded individuals, which might result in issues when selecting participants for research or clinical trials.	ICD codes for ovarian cancer (0.901 vs 0.814), lung cancer (0.859 vs 0.828), cancer cachexia (0.862 vs 0.650), and lupus nephritis (0.959 vs 0.855) had higher F1 scores on the gold testing subgroup. The baseline method, which simply analyzes structured data, performs worse with a decrease in F1 score (Ovarian Cancer: 0.901 vs 0.719, Lung Cancer: 0.859 vs 0.787, Cancer Cachexia: 0.862 vs 0.838, Lupus Nephritis: 0.959 vs 0.785).
[59]	National Trauma Data Bank	eXtreme Gradient Boosting model (XGBoost)	Used ICD-10 injury codes with ML approaches to develop models whose performance was compared to that of TRISS.	Results showed that 1,338,417 (96.9%) of 1,380,740 patients were discharged. Deaths were older and had more penetrating injuries (18.0% vs 9.44%). The base XGBoost model outperformed TRISS in receiver-operating characteristic (ROC) (0.950 vs 0.907) across subpopulations and secondary populations.
[54]	PHS and MIMIC-III EMRs	NLP software NILE and UNITE algorithm.	Medical billing and EMR-based research require correct coding. Scientists have been utilizing supervised techniques to automatically assign ICD codes from clinical notes. Since they use hospital EMR ICD code data, supervised approaches are susceptible to practice and coding biases, making it problematic to port trained supervised algorithms to other EMR systems.	Comparable to LR and MLP, UNITE achieved an AUC of 0.91 at PHS and 0.92 at MIMIC across 6 disorders. It outperformed subject models by a wide margin and consistently outperformed LR, topic models, and neural network models across many EMR platforms, demonstrating its adaptability.
[4]	MIMIC II & MIMIC III	Hierarchical Attention bidirectional Gated Recurrent Unit (HA-GRU), SVM, CBOW and CNN, and NLP methods Tokenization, Hierarchical Segmentation	The study focused on the EHR's unstructured data, zeroed down on three features: (a) lengthy documents (instances), (b) a multi-label configuration (up to 20 labels per instance), and (c) a very big label collection (6,500 distinct ICD9 codes and 1,047 3-digit unique ICD9 codes). The research explored how to address these aspects collectively, especially in the therapeutic setting.	Due to the rigorous text tokenization and hierarchical segmentation of the original material, the results show that the Hierarchical Attention GRU architecture outperforms the SVM, CNN, and CBOW models while maintaining the whole input text and offering excellent transparency.
[37]	NCCH	SVM, NB, DT, kNN, RF, AdaBoost, and MLP classifiers are compared.	The research compares and contrasts pattern matching, rule-based, and machine-learning approaches to determine which computational strategy is best for auto-coding using ICD-10AM and ACHI. The study focused on two chapters of ICD-10-AM, representing the code sets for respiratory and gastrointestinal disorders.	DT and AdaBoost classifiers outperform other classifiers with a Precision of (0.92062, 0.92392), F-score of (0.87305, 0.91412), Accuracy of (0.79201, 0.86118), and Jaccard Similarity of (0.74537, 0.82945).

12. Advancements in AI Techniques for Disease Classification using ICD, NLP and, Deep Learning on EHRs

This chapter delves deeper into the utilization of AI techniques with the ICD based on EHRs. Specifically, five studies focused on employing Deep Learning and NLP techniques in disease classification and diagnosis are discussed, building upon earlier works.

An ICD-10 classification model and the platform for automated ICD-10 prediction and training: For their ICD-10 classification model, Pei-Fu Chen et al. relied on NLP and a DL model. Data processing, model construction, feature extraction, model training, and the development of a b service make up the entirety of the foundation for creating a system. In this study, the whole process of the ICD-10 coding and training system. the network architecture used to build the classification model, which consists of 4 neural network layers and features both a Recurrent Neural Network (RNN) and a Fully Convolutional Neural Network (FCNN). Performed two separate classification procedures, with a total of 14,602/9780 CM/PCS labels in the NTUH data records [16].

A Deep Learning system for automated ICD coding based on knowledge and attentiveness: The data for this study came from two sources: clinical notes and ICD headings. First, the words in a clinic note are encoded using A knowledge attention-based deep learning framework for automatic ICD coding (KAICD), and then extracted using a multi-scale CNN; second, the attention-based Bi-GRU is used to generate a knowledge library of all ICD titles. from Yifan Wua et al [63] depicts the proposed system. Consists of four distinct stages. database containing all ICD titles' knowledge mechanism for knowing attention creation A- Raw clinic notes are first processed B - Extraction of features from clinic notes. The attention approach is employed to get these information vectors from the knowledge database because some ICD titles are more important to include in clinic notes than others. The clinic note features and knowledge vectors are then merged to create the classifier's input. In the end, the likelihood of each ICD code is determined using the fully connected layer with sigmoid activation. Modern alternatives are surpassed by micro-precision of 0.502, micro-recall of 0.428, and micro-f1 of 0.462. According to ablation results, ICD title features trained using attention-based Bi-GRU improve feature expression and performance while features acquired from clinical notes using a multi-scale CNN are essential to our model. Additionally, when utilized as a pre-training technique for word embedding, Skip-Gram performs better than CBOW and GloVe.

Automatic ICD-10 Coding using a Deep Learning Framework: Recently, Deep Learning techniques have been used to revive the use of automated systems for coding diagnosis. In this study, To automatically assign ICD-10 codes to raw text in French discharge summaries, Abdelahad CHRAIBI et al. developed a model utilizing Deep Learning and NLP approaches. This research used a database of over 134,000 EHRs. The 108 thousand hospitalizations bet en January 1, 2016, and March 31, 2019, for which ICD-10 diagnostic codes re assigned, are represented by the chosen DSs.To create a vast corpus of raw French text spanning several medical disciplines, all reports have been mechanically de-identified using NLP methods including (entity recognition) and (regular expressions).

Used a pipeline that includes the following key processes to generate the classification model: text preprocessing, feature engineering, data splitting, parameter t aking, and model generation. Using a real-world dataset, several ANN was trained to distinguish bet en four distinct types of guest-stay length. While there are hundreds of ICD-10 codes, focused on the 613 most often used ones since they had the highest predictive effectiveness. The overall average accuracy of our method was 83%, and this was measured across 346 diagnostic codes from various medical units. The Medical Information Department (MID) doctors who re responsible for vetting our findings received the ultimate seal of approval [17].

Deep-ADCA: The study conducted by Jakir Hossain Bhuiyan Masud et al. [46] focused on data collection from a university teaching hospital in Taipei, Taiwan, covering the period from January 1st, 2016, through December 31st, 2016. The researchers retrieved information from this hospital's Electronic Medical Records (EMRs) for analysis. Patients with missing clinical notes were not considered, resulting in the inclusion of twenty-one thousand nine hundred and fifty-three patient records from five specialties, including cardiology, neurology, nephrology, metabolism, and psychology.

Data Pre-Processing, as the second part of the study, involved addressing the varying lengths of clinical notes and eliminating certain irrelevant details to improve the quality of the data for creating a Deep Learning model. The researchers initiated a ”text cleaning” procedure, eliminating punctuation and numbers. Additionally, they removed ”stop words” such as ”a,” ”an,” ”and,” ”for,” ”it,” and ”the” due to their limited predictive value. The data underwent pre-processing, which included stemming and TF-IDF (term frequency-inverse document frequency) vectorization. In the third part, feature extraction was performed using the Word2Vec method to generate embeddings for individual words. This technique takes a text corpus as input and automatically generates a vector representation for each word. The Word2Vec method can create a dispersed representation of words through either the continuous bag of words (CBOW) or skip-gram model.In the fourth part, the researchers developed a model for predicting ICD-10 codes using a CNN classification network. The Deep Learning model utilized 90% of the data for training and the remaining 10% for testing purposes.

BW_att: In this research, we considered the possibility of using Deep Learning for automated Coronary Heart Disease (CHD) coding. Shuai Zhao et al. [66] developed the BW_att model, which is a Deep Learning technique aiming to achieve fully automated CHD coding by combining elements from three different models. The first element is a BERT variant module that encodes medical documentation. To address the issue that BERT variants typically cannot handle sequences longer than 512 tokens, we devised a truncation strategy and fine-tuned BERT variants using masked language models on the clinical text. The second element is a Word2Vec encoder for code titles, and the third element is a label-attention integrator for embeddings in clinical text and code titles. The experimental results showed that for most of the coding missions, BW_att outperformed certain well-studied baselines, achieving 96.2% Macro-F1 for the top 100 codes in Fuwai-CHD and 40.5% Macro-F1 for the top 50 codes in MIMIC-III-CHD, respectively. Additionally, BW_att was able to identify clinical text tokens that are useful for target code prediction. In conclusion, BW_att demonstrates considerable promise as a practical tool for CHD coding.

Accurately classifying diseases is paramount in healthcare for effective diagnosis, treatment, and research. Researchers have recently explored innovative approaches combining the ICD codes, NLP, and

Deep Learning techniques to automate disease coding, improve accuracy, and reduce human involvement.

Table 5 presents an overview of disease classification studies that have employed ICD, NLP, and Deep Learning in various medical datasets. The table summarises key findings from each study, including the reference, dataset used, the approach employed, the objective of the research, and the corresponding results.

TABLE 5. Disease Classification with ICDs, NLP, and Deep Learning: An Overview

Reference	Dataset	Approach	Objective	Result
[16]	NTUH	NLP methods: global vectors, word-to-vector conversions, language model embeddings, and single-head attention recurrent neural networks with transformer-based bidirectional encoder representations.	Creates a Deep Learning model for ICD-10 coding with the goal of having the model create diagnostic and procedure codes automatically from free-text medical notes in order to decrease the need for human involvement and improve accuracy.	Medical dataset with transformer-based bidirectional encoder representation achieved F1-scores of 0.715 and 0.618 for ICD-10 Clinical Modification code and Procedure Coding System code in the RNN Unit classification model.
[63]	MIMIC III	Multi-scale CNN, attention-based Bi-GRU	Conventional ML-based ICD coding ignores extracting features from ICD titles. KAICD system effectively utilizes clinical documentation and ICD-10-CM/PCS codes.	KAICD achieves micro-precision of 0.502, micro-recall of 0.428, and micro-f1 of 0.462 when it is evaluated on the publicly available dataset MIMIC III, outperforming other competing approaches.
[17]	134,000 EHRs from January 1, 2016, to March 31, 2019.	NLP techniques including entity recognition techniques and regular expressions, and Artificial Neural Networks.	An automated coding method to aid doctors in the process of adding ICD codes to EHRs.	On average, our method had an 83% success rate in predicting 346 diagnostic codes from various medical specialties. Doctors working in the hospital's coding division of the MID confirmed our findings.
[46]	EMR data from a Taipei, Taiwan teaching hospital.	NLP techniques, like global vectors, word-to-vector conversions, and embedding methods, are combined with Deep Learning CNN models.	Enhance clinical decision-making and service quality by using a Deep Learning-based NLP model and a growing CNN model to reliably predict ICD-10 codes.	In clinical trials, the CNN model scored well in all five divisions (Precision: 0.50-0.69, Recall: 0.78-0.91). With 69% accuracy, 89% recall, and 78% F-score, the CNN model fared best in the cardiology category.
[66]	Fuwai-CHD and MIMIC-III-CHD	Word2Vec, a label-attention module, and a BERT variant module	Intended to develop a Deep Learning-based system for automating the coding of CHD.	High accuracy for top 100 codes in Fuwai-CHD (Macro-F1: 96.2%, Macro-AUC: 98.9%). Lower performance for top 50 codes in MIMIC-III-CHD (Macro-F1: 40.5%, Macro-AUC: 66.1%).

13. Conclusion

In conclusion, this survey provides valuable insights into the crucial role of ICDs in health and study. The widespread use of the ICDs in various datasets for research, clinical decision-making, general health monitoring and healthiness policy analysis underscores its importance in medicine. Notably, previous research has delved extensively into the application of ICD-10 codes, focusing on their relevance in COVID-19. These studies have diligently examined the positive predictive value of ICD-10 codes and assessed the accuracy of reported mortality, showcasing the significance of accurate disease coding in health crises.

The ICD-10 and its applications have proven pivotal in enhancing healthcare outcomes and public health through standardized disease classification and data analysis. Its role in facilitating seamless communication and data exchange within the healthcare industry cannot be overstated. As EHRs have gained prominence in modern healthcare systems, the need for advanced techniques in text processing has become evident. Integrating NLP approaches has enabled more efficient handling and analysis of clinical data, paving the way for improved disease coding and classification.

Moreover, the synergy between NLP techniques and Machine Learning and Deep Learning algorithms has further revolutionized disease coding in the context of ICD. The success stories shared in the literature bear witness to the immense potential of these cutting-edge techniques in automating and streamlining disease coding processes. Their application has proven indispensable in healthcare settings, alleviating the burden of manual coding tasks, reducing errors, and enhancing overall efficiency. As AI and Deep Learning advance, it holds great promise for further enhancing disease coding and classification within the ICD system. Leveraging these advancements and integrating NLP techniques will undoubtedly open new avenues for more accurate and sophisticated disease classification.

In conclusion, this survey serves as a comprehensive resource highlighting the paramount importance of the ICD and its continuous evolution in the ever-changing healthcare landscape. It emphasizes the significance of accurate disease coding and classification for informed decision-making, effective public health management, and improved healthcare outcomes. By shedding light on the synergistic combination of NLP, Machine Learning, and Deep Learning techniques, this survey demonstrates how these tools can revolutionize disease coding processes and contribute to advancing healthcare practices. The future of ICD-based disease classification appears promising as new technologies and methodologies continue to drive innovation in the field. Ultimately, embracing these advancements will enable healthcare professionals to harness the full potential of ICD, paving the way for enhanced disease management and improved overall health and well-being.

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