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*Research article*

# Design and implementation of a smart Internet of Things chest pain center based on deep learning

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**Abstract:** The data input process for most chest pain centers is not intelligent, requiring a lot of staff to manually input patient information. This leads to problems such as long processing times, high potential for errors, an inability to access patient data in a timely manner and an increasing workload. To address the challenge, an Internet of Things (IoT)-driven chest pain center is designed, which crosses the sensing layer, network layer and application layer. The system enables the construction of intelligent chest pain management through a pre-hospital app, Ultra-Wideband (UWB) positioning, and in-hospital treatment. The pre-hospital app is provided to emergency medical services (EMS) centers, which allows them to record patient information in advance and keep it synchronized with the hospital's database, reducing the time needed for treatment. UWB positioning obtains the patient's hospital information through the zero-dimensional base station and the corresponding calculation engine, and in-hospital treatment involves automatic acquisition of patient information through web and mobile applications. The system also introduces the Bidirectional Long Short-Term Memory (BiLSTM)-Conditional Random Field (CRF)-based algorithm to train electronic medical record information for chest pain patients, extracting the patient's chest pain clinical symptoms. The resulting data are saved in the chest pain patient database and uploaded to the national chest pain center. The system has been used in Liaoning Provincial People's Hospital, and its subsequent assistance to doctors and nurses in collaborative treatment, data feedback and analysis is of great significance.

**Keywords:** chest pain center; Internet of Things (IoT); deep learning

## 1. Introduction

In recent years, there has been a growing number of cardiovascular patients in China, among whom acute myocardial infarction (AMI) accounts for a high pre-hospital mortality rate. Both the incidence rate and mortality are increasing, and chest pain is the primary symptom. Chest pain is a common clinical symptom among emergency department patients, often accompanied by serious diseases such as AMI, pulmonary embolism and aortic dissection, resulting in high mortality rates [1]. Therefore, the establishment of a chest pain center is extremely important. However, in the current traditional chest pain centers in China, patient information cannot be collected promptly during the patient visit process at various hospitals. Chest pain centers lack proprietary databases, management functions, and place a heavy workload on medical staff, which has become an increasingly prominent challenge. Cardiovascular diseases have been extensively studied by researchers in the field of medical imaging. For instance, Wang et al. [2] conducted a detailed investigation into image segmentation techniques. Nevertheless, there is currently a limited amount of literature available regarding the study of chest pain data.

Data entry for chest pain centers has always been a key task for various hospitals, as it is an effective means of quality control and improvement of diagnosis and treatment quality for chest pain centers. Generally, four kinds of data need to be filled in, including patient basic information, emergency information, chest pain diagnosis and treatment and patient outcomes. Basic information contains name, age and ID number, while emergency information generally denotes patient condition, assessment, vital signs, mode of arrival and pre-hospital thrombolysis therapy. Chest pain diagnosis and treatment entail the results of various hospital examinations, including electrocardiograms, laboratory tests, cardiology consultations, diagnosis, initial medications, Global Registry of Acute Coronary Events (GRACE) assessment, re-risk stratification and treatment strategies. The catheterization room includes the patient's surgical information. Patient transfer encompasses patient discharge information, diagnosis and medication used during hospitalization, providing a comprehensive analysis of patient medication. However, the current data collection and entry for chest pain patients have not attained intelligent automation. Most hospitals collect various data manually, which is time-consuming, laborious and prone to errors.

China has a large population base, with prominent issues such as imbalanced development of medical resources and resource scarcity. With the fast development of internet technology, combining chest pain centers with internet technology provides a solution to the inadequate development of medical information. There are already many information systems used for the daily management of chest pain centers in China. Among them, the "Bian Que Emergency Rescue" pre-hospital emergency system and the "Renxin Xia" chest pain center are relatively mature in information management [3]. The "Bian Que Emergency Rescue" system emphasizes pre-hospital treatment and establishes connections between the 120 ambulance and the emergency center. "Renxin Xia" focuses on the patient's diagnosis and treatment process, realizing the tracking of the patient's medical treatment trajectory, recording the treatment process and reducing the workload of medical personnel. Currently, some hospitals in China have adopted such systems for chest pain treatment [4]. However, most current systems do not have adequate docking functions with the hospital's diagnosis and treatment system, thus they are incapable of automatically and intelligently obtaining clinical information for the chest pain center.

Denysyuk et al. [5] provided a comprehensive overview of algorithms for the automatic recognition of cardiovascular diseases based on electrocardiogram (ECG) data. They found that most studies employed convolutional neural networks and support vector machine techniques, which exhibited outstanding performance in disease prediction. Addressing a large number of patients' health data, Costa et al. [6] introduced a decentralized software model based on blockchain and intelligent control for identity recognition. In the field of medical Internet of Things (IoT), Chen et al. [7, 8] established an IoT-based regional collaborative emergency response system for patients with ST-segment elevation myocardial infarction, resulting in significant reductions in patients' treatment time and mortality rates. Additionally, IoT has found wide-ranging applications in the field of engineering. Cao et al. [9] integrated IoT with the structural health assessment of building information, utilizing Building Information Modeling (BIM) tools to retrieve, acquire, organize and store building data. In terms of algorithmic research, Ma et al. [10] employed a hybrid Grey wolf optimizer (GWO)-Extreme machine learning (ELM) algorithm to characterize composite bridges, enhancing the accuracy, speed and precision of detection. To address degradation issues in steel-concrete structures under high temperatures, Morasaei et al. [11] employed intelligent analytical techniques for prediction, validating the superiority of ELM-GWO technology in split tensile load scenarios. Tajziehchi et al. [12] investigated seismic control and optimization through genetic algorithms, achieving the intended outcomes. Drawing from both domestic and international research, the interdisciplinary intersection of engineering and medicine has attracted significant attention. This article aims to extract symptoms from electronic medical records of chest pain cases. However, due to the distinctive and intricate nature of Chinese electronic medical records, conventional retrieval methods have proven inadequate in achieving the intended results and have also consumed substantial time and effort. Notably, researchers have yet to explore entity recognition in the context of chest pain symptoms. We employed the Bidirectional Long Short-Term Memory (BiLSTM)-Conditional Random Field (CRF) model algorithm to extract electronic medical records of chest pain patients and applied it to the Smart Chest Pain Center, achieving marked advances in both speed and accuracy.

In this paper, we design a deep-learning-based IoT system for chest pain management in both pre-hospital and in-hospital services. Assisted by this system, doctors can obtain patient information such as electrocardiogram and vital signs before the patients arrive at the hospital, allowing for early diagnosis and preparation for percutaneous coronary intervention (PCI) treatment. The system enables easy extraction of patient's personal information and medical process data, including time information, clinical diagnosis, laboratory tests, auxiliary examinations and drug therapy, thus apparently reducing manual input and realizing the intelligent extraction of chest pain data. Furthermore, the deep learning algorithm is used to extract electronic medical records, surgical information and smoking history of patients with chest pain, with a recognition rate of over 93%, improving the intelligence level of data recording. The proposed system provides rapid diagnosis, assessment and treatment coordination for chest pain symptoms, which aligns with the future development philosophy of intelligent chest pain centers [13].

## 2. Design concept

The construction of the information system is a critical part of the chest pain center [14, 15]. Currently, most hospitals have not attained paperless reporting and management of chest pain information. Reporting a single patient's data often requires a large amount of manual input and can only be completed after the patient consultation is over, which is prone to errors and time-consuming, potentially leading to problems such as delayed emergency treatment. To address these issues, we propose a new Smart IoT Chest Pain Center information system. The designed system consists of three layers: the perception layer, network layer and application layer, whose architecture diagram is shown in Figure 1.

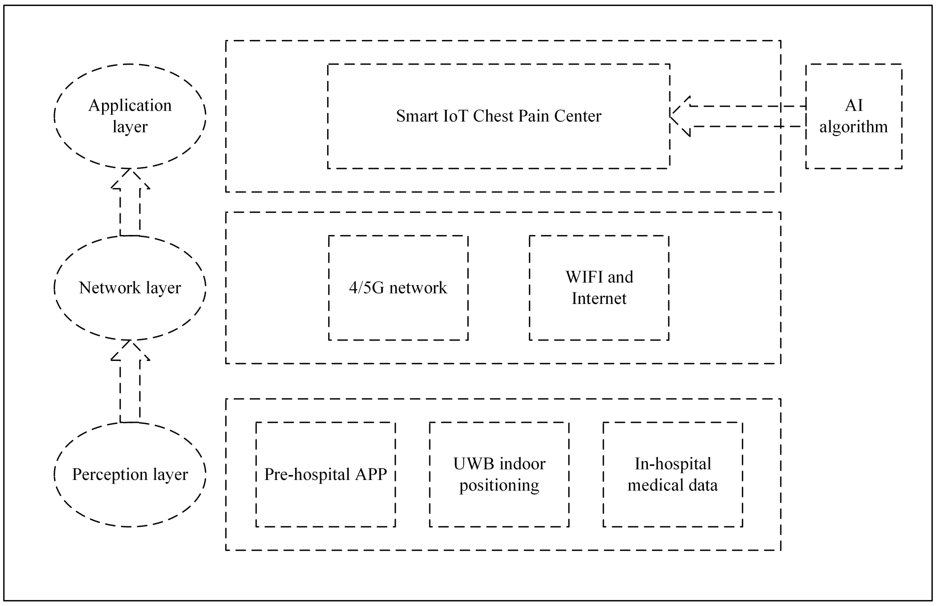


**Figure 1.** Architecture diagram of Chest Pain Center.

The perception layer includes the pre-hospital Application(APP), Ultra-Wideband (UWB) indoor positioning system and in-hospital medical data. The network layer consists of a 4G/5G network, Wi-Fi, and the Internet. The application layer is the chest pain patient data management system, which establishes a standardized chest pain database. The system integrates data from the perception layer through positioning algorithms, hospital data extraction and fusion algorithms, intelligent medical history and medical record analysis and patient data quality monitoring algorithms. The data is then uniformly saved to the chest pain patient database and uploaded to the national chest pain center platform by the chest pain management team. Through this system, doctors can promptly judge the patient's condition, which saves valuable time for the treatment of chest pain patients. It also provides better quality control technology means for the scientific management of chest pain information in the future [16].

Our objective is to address the following issues:

1) Manual reporting issue: The current manual reporting method leads to time-consuming data entry for patients and is susceptible to errors. Our Smart Chest Pain Center system eliminates the necessity for manual reporting through automated data collection.

2) Delay in emergency response: Due to the time required for manual reporting, there could be delays in providing medical care to emergency patients. With real-time data collection and database

management, our system enables doctors to rapidly assess patient conditions, providing valuable time for patient treatment.

3) Data integration issue: During the process of data collection both pre-hospital and in-hospital, data from different sources exist. Our Chest Pain Center achieves integration of data from the perceptual layer into a unified chest pain patient database through data extraction.

4) Extraction of Chinese electronic medical records issue: Extracting symptoms from Chinese electronic medical records is currently a challenge. We employ deep learning techniques to extract symptoms from chest pain patients and apply them within the Smart Chest Pain Center system, increasing the intelligence of the chest pain center.

## 3. Design and implementation of perception layer and network layer

### *3.1. Pre-hospital app system*

Before patients receive medical treatment, healthcare professionals can enter patients' basic information such as name, gender, age and contact details in the pre-hospital APP system. They can also record critical information like onset time and vital signs. Additionally, healthcare providers can upload patients' emergency ECG data through the APP. These data will be transmitted through the system for remote diagnosis and urgent medical guidance.

After patients arrive at the hospital and complete their medical treatment, healthcare professionals can use the refresh function to instantly retrieve the information entered in the pre-hospital APP system. This intelligent extraction feature significantly simplifies the data collection and organization process, enhancing the efficiency of medical personnel. It allows them to focus more on patient treatment and care. Moreover, this pre-hospital APP system is closely integrated with the hospital's database. During the patient's medical visit, the system continuously obtains real-time diagnostic information, emergency data, ECG readings, troponin levels and other critical data indicators, as well as key information regarding chest pain diagnosis and outcomes [17]. This timely acquisition and integration of data provides healthcare providers with comprehensive and accurate patient records, aiding in more precise diagnosis and treatment decisions. Furthermore, the system is also connected to the reporting interface of the National Chest Pain Center.

In summary, the pre-hospital APP system plays a pivotal role in the emergency medical process. Through intelligent information collection and transmission, it enhances the efficiency and accuracy of emergency response, assisting medical personnel in providing better patient care and treatment. Its close integration with hospital databases and the National Chest Pain Center offers effective means for information sharing and data monitoring. As the application scenarios expand, the pre-hospital APP system is expected to play an even larger role in the field of emergency medical care, safeguarding patients' health and well-being.

The pre-hospital APP makes several significant contributions:

1) Timely recording of personal information for pre-hospital patients, including electrocardiogram data, vital signs, medication, treatment methods and other relevant information.

2) Prompt feedback on the patient's method of arrival and the information of the 120 emergency medical service vehicles for patients with chest pain.

3) Timely recording of vital sign data such as the patient's current level of consciousness, breathing, pulse, temperature, heart rate and blood pressure.

4) Data input for key information, such as drug names, dosage concentration and administration time, for patients with acute coronary syndrome (ACS).

### *3.2. UWB positioning system*

UWB positioning is a technology that uses Ultra-Wideband (UWB) technology to measure location and tracking. It is a feasible method for indoor positioning due to its high accuracy and strong anti-interference ability. The UWB positioning system of the Smart Chest Pain Center consists of base stations, tags and wristbands. Base stations are installed in the emergency hall, catheterization room and doctor's office; tags are worn by doctors, and wristbands are worn by patients. All base stations are connected to the hospital server through a gateway and communicate with the hospital server using the WebSocket network protocol. In the past, healthcare professionals typically had to manually record patients' appointment times, a process that was not only time-consuming but also prone to errors. The primary goal of the UWB positioning system is to achieve patient localization and accurate timestamp acquisition during their treatment within the hospital premises. This aims to provide the medical team with a more efficient workflow and more precise data recording. By utilizing the high-precision localization capabilities of UWB technology, this system can accurately track patients' positions and movement trajectories, associating them with specific treatment times. This integration improves the quality of medical management and contributes to enhanced patient care and accurate record-keeping.

#### 3.2.1. Hardware system function design

Hardware devices in the emergency room, catheterization laboratory, doctor's offices and the triage desk all employ zero-dimensional positioning to capture the times when patients and doctors enter their respective rooms. At this juncture, the data is transmitted to the hospital's internal network via the User Datagram Protocol (UDP) protocol and forwarded to the hospital's internal server. The hardware calculation engine on the hospital server receives the data collected by the hardware, calculates the corresponding actual location data and transmits the location data to the hardware receiving program using the Transmission Control Protocol (TCP) protocol. Subsequently, the hardware receiving program conveys the location data to the software backend through WebSocket.

#### 3.2.2. Hardware deployment

The hardware is deployed respectively in the emergency hall, catheterization room, doctor's consultation room and triage desk. Among them, the catheterization room, doctor's consultation room and triage desk are powered and networked using Power over Ethernet (POE) switches, while the emergency hall is powered by a 5V-1A power supply and connected to the information technology switch.

#### 3.2.3. Computing engine deployment and hardware receiving procedures

The computing engine is deployed on an internal server within the hospital and is capable of monitoring and managing devices. Please refer to Figure 2 for the computing engine. This hardware receiving program is deployed on the hospital's internal server. It intelligently collects patient appointment timestamps by utilizing information gathered through wristbands worn by patients and hardware devices. The collected data is then transmitted to the server. Additionally, the location information computed by the calculation engine can be transmitted to the software backend using the WebSocket protocol.

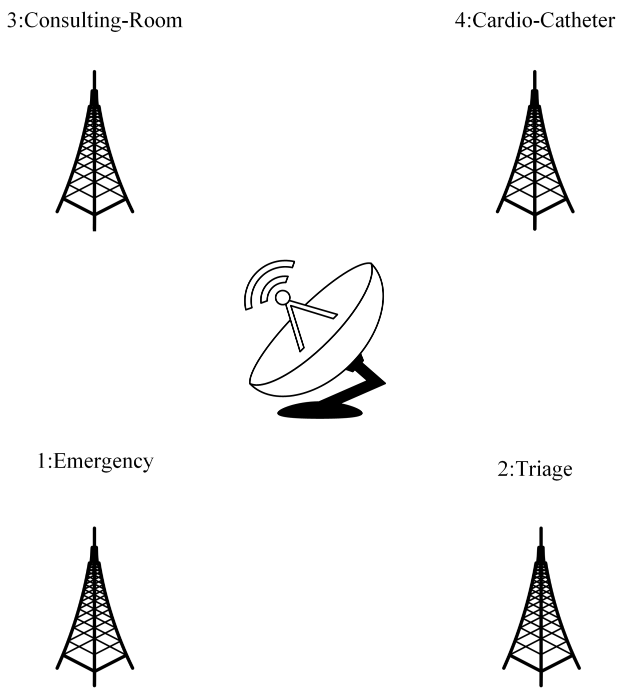


**Figure 2.** Computational engine simulation diagram.

3.2.4. Display of hardware equipment.

The hardware devices primarily consist of employee badge tags, wristband tags, and base stations. Among these, the employee badge tags are carried by healthcare personnel and are used to associate with patients' wristbands. The base stations are responsible for receiving patients' in-hospital information at various time points, such as the initial treatment time. These base stations are connected to upload this data to the database swiftly and accurately. This enables the rapid and precise acquisition of timestamp information for chest pain patients, as illustrated in Figure 3.


**Figure 3.** Hardware equipment display.

### *3.3. In-hospital patient treatment system*

This system extracts all data related to patients within the hospital, including their gender, age, medical history, medication information, results of in-hospital examinations and surgical information, among others. The data are managed through standardization to prepare for intelligent extraction and smart medical care in the next steps. After logging in, users can select to add a patient and filter patients based on conditions. Once imported into the database, all of the patient's in-hospital data can be obtained, and doctors can enter the patient information interface to view and modify their information. The system has an intelligent refresh function that can obtain real-time data on the patient's visit, and the data enters a locked state after being submitted for review by the corresponding reviewer.

On the chest pain patient list interface in each department, patient names, genders and ages can be viewed. After entering the patient's information, operations such as adding, deleting, modifying and querying can be carried out, and complete intelligent extraction of basic information, chest pain diagnosis and treatment, surgical information and patient outcomes are fully implemented. Among them, electrocardiograms can be uploaded to the database via photo-taking to support subsequent analysis of the electrocardiogram. The automatic import function can interact with the backend to import data into the database, and the automatic extraction rate can reach 97%. Figures 4 and 5 show the framework diagram of mobile APP and chest pain filling website.

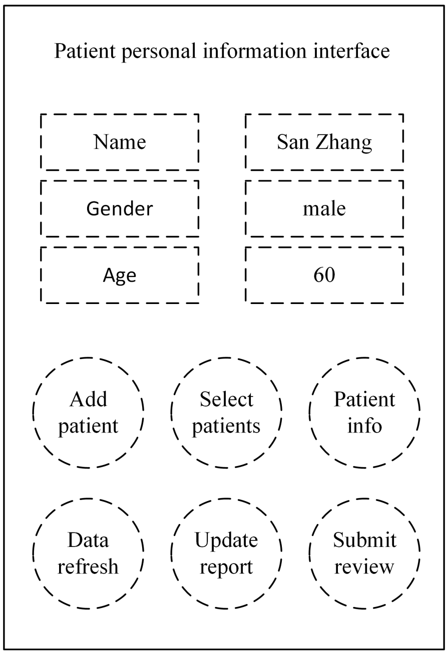


**Figure 4.** Mobile phone APP interface frame.

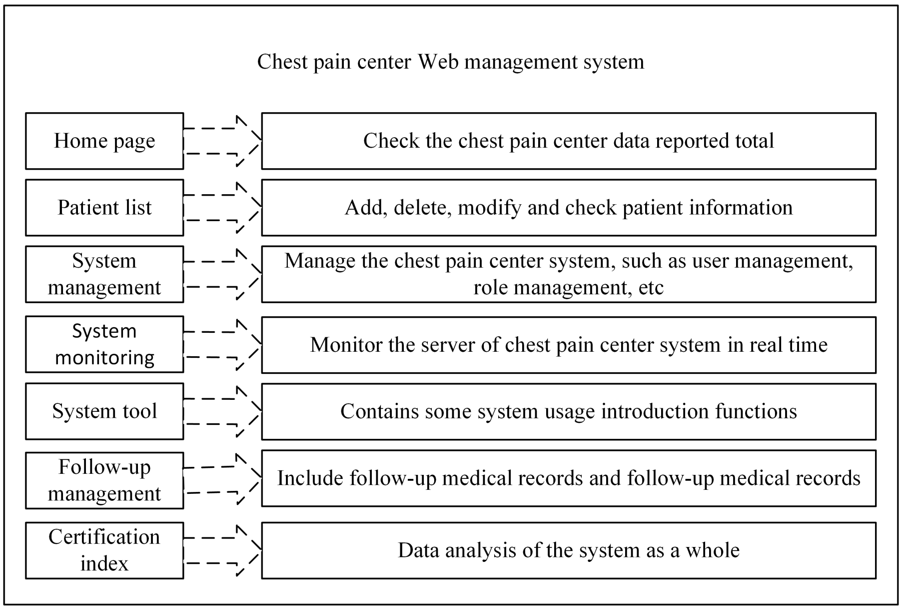


**Figure 5.** Chest pain website interface frame.

### 3.3.1. Data refresh function

After the patient is admitted, all the current patient data within the hospital can be accessed. By refreshing the data, the patient's complete information within the hospital can be retrieved again to prevent incomplete information.

#### 3.3.2. Data reporting/update reporting function

Once the patient's information is obtained, healthcare workers can submit the data. If the patient has not been previously reported, this function can directly transmit the information to the national website. If the patient has already been reported, subsequent updates will be made through further reports.

#### 3.3.3. Submit for review function

After the data is submitted, healthcare workers can proceed to submit it for review, which includes quality control functions. Certain data that does not meet the specified requirements will be restricted from being submitted for review. These conditions encompass instances where the preliminary diagnosis time is not earlier than the first medical contact time, the first medical contact time is not earlier than the arrival time at the hospital gate, the first electrocardiogram time is not earlier than the first medical contact time and the difference between the electrocardiogram diagnosis time and the electrocardiogram time does not exceed 10 minutes. Additionally, the period between the completion of the blood draw and the receipt of the troponin testing report should not surpass 20 minutes. The timeframe from the first medical contact to the completion of the initial electrocardiogram should not exceed 10 minutes or be less than 3 minutes. It is imperative that antiplatelet therapy is not administered prior to the preliminary diagnosis time. Once the patient's data fulfills these conditions, it can be submitted to the reviewer with a single click.

#### 3.3.4. Chest pain assisted decision-making

The module is divided into three parts: Grace, Heart (the full name of a medical heart scoring system), and Wells (the full name of a clinical possibility score of medical pulmonary embolism). It can assist healthcare professionals in quickly analyzing corresponding symptoms of chest pain. The Grace score can intelligently receive personal information of the patient and automatically calculate the Grace score for that patient, as shown in Figure 6.

The GRACE score is a method currently utilized in the medical community to assess the risk level of unstable angina and acute non-ST elevation myocardial infarction [18–20] in ACS. It serves as a medical calculation tool for designing chest pain treatment plans and provides an effective foundation for risk stratification and individualized treatment of ACS patients. In the current GRACE scoring system, it typically necessitates manual input of patient information, including age, heart rate, systolic blood pressure, serum creatinine and heart function classification, to derive the scoring result. However, our system automates the retrieval of patient information through in-hospital examinations, achieving intelligent processing of information. This automation significantly reduces unnecessary steps for inputting information.

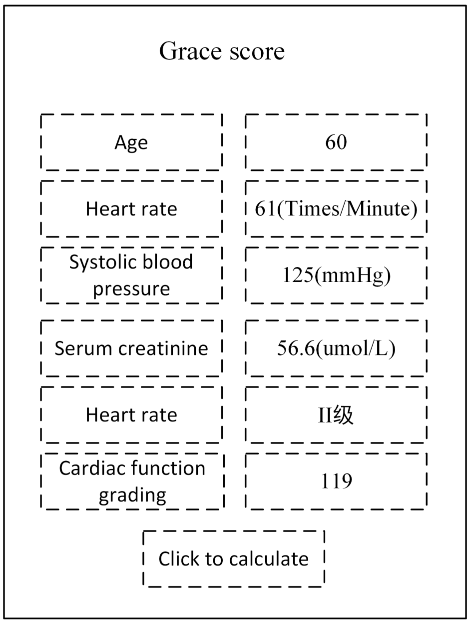


**Figure 6.** Grace score.

The HEART score comprises five indicators: history (H), electrocardiogram (ECG, E), age (A), risk factors (Risk factor, R), and troponin (T). The HEART score allows for early identification of high-risk acute coronary syndrome in emergency chest pain patients, providing valuable treatment time. To optimize the utilization of the HEART scoring system, we have integrated it as an auxiliary decision-making tool for chest pain cases. Our goal is to enhance the diagnostic and treatment process for emergency chest pain patients and improve medical efficiency. Initially, we integrated the HEART scoring algorithm into our in-hospital system, enabling the tool to perform automated calculations. When healthcare providers receive emergency chest pain patients, they simply input relevant data such as medical history, electrocardiogram, age, risk factors and troponin levels. The system then automatically calculates the HEART score, swiftly providing the scoring result. This automation not only saves time and effort for healthcare providers but also reduces potential errors inherent in manual calculations. By utilizing the HEART score as a chest pain decision-support tool, we can effectively enhance the efficiency and accuracy of triaging emergency chest pain patients. This aids healthcare providers in early identification of high-risk acute coronary syndrome cases, enabling timely and effective treatment measures. Ultimately, this approach maximizes patient safety and well-being.

The Wells score is a clinical symptom rating system used to assess the probability of pulmonary embolism in patients. It serves as a diagnostic tool for suspected acute pulmonary embolism cases. By integrating the Wells scoring algorithm into the hospital system, we achieve automated scoring for suspected pulmonary embolism cases. When healthcare providers encounter patients with suspected pulmonary embolism, they can input relevant clinical symptoms and indicators, such as malignancy, heart rate, clinical signs and physical examination findings into the system. The system will automatically calculate the Wells score based on this data and provide the corresponding risk level. This enables healthcare providers to promptly assess the patient's risk of experiencing pulmonary embolism, facilitating diagnostic and treatment decisions. Additionally, integrating the laboratory examination system with the Wells scoring system allows for the automatic import of test results like heart rate. By combining the Wells score with the hospital system, we effectively enhance the efficiency and accuracy of diagnosing acute pulmonary embolism. This approach improves the diagnostic and treatment capabilities for acute pulmonary embolism patients, ultimately safeguarding patients' lives and health.

### 3.3.5. Quality control and management

This system includes functions for quality control and management, allowing users to view patient records on a daily, weekly, monthly and yearly basis. It analyzes symptoms associated with chest pain diagnosis and offers comprehensive quality control reminders, timelines and intelligent icons corresponding to monitored patient data. This equips medical staff with pertinent chest pain symptom patterns for subsequent analysis and reference, thereby enhancing the reporting quality of the chest pain center. Quality control and management involves the following three steps:

1) Data collection: Establish a comprehensive data collection and recording system to ensure accurate, comprehensive and timely recording of information for all chest pain patients. This includes patient demographics, symptoms, vital signs, laboratory test results, electrocardiograms and other relevant data.

2) Data organization: Establish standardized chest pain patient diagnostic and treatment workflows along with emergency guidelines. Clearly define the specific requirements and time targets for each step. Healthcare personnel should follow these workflows, from patient reception and assessment to diagnosis and treatment, ensuring that every patient receives standardized, high-quality medical care.

3) Quality metrics and evaluation system: Develop quality metrics and evaluation criteria for chest pain patients to monitor and assess the quality of medical services. These metrics may include patient wait times, outcomes of chest pain patients, emergency response times and other key indicators. Regular evaluations and improvements based on identified issues help enhance the quality of medical services.

Below is a data report for the chest pain center from October 2022 to March 2023, with the symptoms of patients' chest pain diagnoses displayed on the right, as shown in Figure 7.

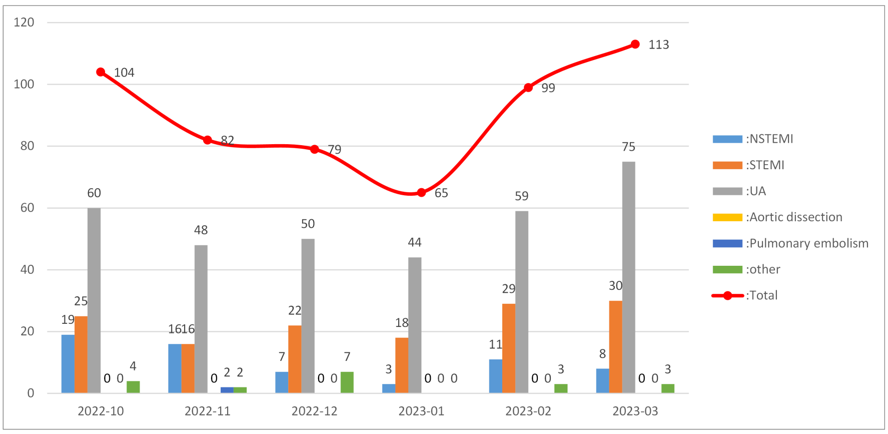


**Figure 7.** Quality control information statistics chart.

The timeline can display patient timestamps in real-time, highlighting any non-compliant time points with color to prompt healthcare workers to make modifications and reduce error rates. The quality control results are as follows:

1) For all acute chest pain patients admitted through self-service or local emergency medical services (EMS) calls, the time between the first medical contact and the first ECG has been reduced to less than 10 minutes per month.

2) For patients with ST-segment elevation myocardial infarction (STEMI), the time between the end of the first ECG and diagnosis has been shortened to less than 10 minutes per month.

3) A rapid bedside test method for measuring muscle calcium protein has been established, with a turnaround time of less than 20 minutes from blood collection to reporting.

4) 100% of patients initially diagnosed with non-ST-segment elevation myocardial infarction (NSTEMI)/unstable angina (UA) received stratified risk assessment.

5) There is a trend towards a shortened time from diagnosis to the administration of dual antibodies within 10 minutes for all ACS [21] patients.

6) All STEMI [22] patients (except for those receiving first-generation thrombolysis therapy) receive intravenous heparin anticoagulation treatment within 10 minutes after diagnosis.

## 4. Application layer design and implementation

### *4.1. Application layer function*

The server application of this system uses technologies such as Java (1.8), SpringBoot (2.2.13), Mysql (5.7), Mybatis (2.2.4), Redis (6.2.5), and deep learning to achieve standardized management of all chest pain patients at the People's Hospital of Liaoning Province. The technology of deep learning provides intelligent interconnectivity for the chest pain system. We use the HTTP standard to transmit information, leveraging common GET, POST, and PUT requests to enable data viewing and modification functionalities. To ensure data security, we employ JWT (JSON Web Token) technology for data encryption and restrict data requests using tokens. This approach enhances the security and reliability of information transmission. The system also designs a chest pain management database to manage each index of the patients. Among them, the system extracts data from the hospital, automatically calculates the Grace, Heart and Wells scores of patients, and assists doctors in judging the condition of chest pain. It also automatically calculates the D2W (door to wire) time, which is the duration from the patient arriving at the hospital gate to the wire passing through the blood vessels. This is one of the core indicators for evaluating the level of a chest pain center. The intelligent medical history analysis module uses deep learning algorithms to extract and recognize the patient's chest pain electronic medical records, surgical information and smoking history, achieving a high recognition rate and improving the intelligence of data entry. The patient data quality monitoring module monitors the patient's data comprehensively, warns patients with non-compliant data and provides statistics for all chest pain patients in the hospital to help improve the treatment process.

### 4.2. *Implementation of the server*

#### 4.2.1. Server architecture

The server adopts the MVC (Model-View-Controller) architecture, dividing the system into three fundamental components: Model, View and Controller. The View layer implements the display pages of the chest pain system, facilitating patient quality monitoring, and enabling medical staff to view and modify patient information. The Model layer manages all patient information and stores it in a normalized format within the system database. The Controller layer serves as an intermediary between the Model and View layers, governing the flow of the application program.

#### 4.2.2. Database design and implementation

The systematic database design follows the guidelines outlined in the "Certification Standards for Chest Pain Centers in China (6th edition)". Due to space constraints, we present partial fields from two tables within this system: the patient basic information table and the emergency information table. These fields are displayed in Tables 1 and 2, respectively.

**Table 1.** Basic information field table.

| Field name | Field | Type | Length |
|---|---|---|---|
| name | NAME | varchar | 50 |
| gender | GENDER | varchar | 1 |
| age | AGE | int | 10 |
| license number | IDCARD | varchar | 18 |
| phone | CONTACT_PHONE | varchar | 20 |

**Table 2.** First aid information field table.

| Field name | Field | Type | Length |
|---|---|---|---|
| outpatient ID | OUTPATIENT_ID | varchar | 32 |
| hospitalized ID | INPATIENT_ID | varchar | 32 |
| heart rate | HEART_RATE | varchar | 10 |
| body temperature | TEMPERATURE | varchar | 10 |

## 5. Application of artificial intelligence in smart chest pain center

The establishment of an intelligent chest pain management system relies on the support of artificial intelligence. The system utilizes deep learning technology to analyze and process patients' medical records and history. Through the implementation of clinical entity recognition technology [23], the system is expected to achieve the following extractions: AI-based extraction of risk factors for patients with coronary heart disease, clinical symptom extraction of chest pain based on electronic medical record text data and AI-based extraction of surgical information for chest pain patients. Currently, successful extraction of clinical symptoms related to chest pain from electronic medical record text data has been accomplished. The experimental process is outlined below.

### 5.1. Data set

The electronic medical records data for chest pain patients utilized in this study were obtained from Liaoning People's Hospital. A total of ten thousand cases of electronic medical records for chest pain patients were collected. Each medical record document includes the patient's age, disease and diagnosis, common laboratory tests, as well as medical and clinical information during the treatment process.

(1)One day ago, the patient had an attack of chest pain, which appeared as a pinprick, jumping pain, sometimes accompanied by abdominal jumping pain.
(2)The patient suffered sudden loss of consciousness 6 hours ago, and improved after CPR. "Acute myocardial infarction" was diagnosed locally, and coronary angiography was performed to show bilateral lesions.
(3)Nearly 4 days without inducement chest tightness, paroxysmal attacks, including taking the rescue pill can be alleviated, 2-3 hours before the onset of chest pain with deficiency.
(4)Twenty days ago, the patient suffered from chest pain and was diagnosed with acute inferior wall myocardial infarction at the Army General Hospital. He was discharged after medication. 2 hours ago, the patient's symptoms of chest pain recurred and did not relieve, so he came to our hospital as an emergency.
(5)In the past 3 days, the patient repeatedly appeared chest tightness and chest pain after activity, no release, lasting for about 10 minutes without relief, 2-3 times a day; Nearly 2 hours ago, the patient suffered from persistent chest pain with sweating, which became worse than before. He was urgently admitted to Dongling District Hospital and diagnosed with "acute myocardial infarction". He was given oral aspirin 300mg, atorvastatin 20mg, irbesartan 150mg, hypodermic injection of low molecular weight heparin for symptomatic treatment, and then urgently called "120" and transferred to our hospital.
(6)Chest pain 1 hour ago, with chest tightness and shortness of breath, with back pain, with palpitation and dyspnea, with nausea and no vomiting, with acid reflux and no abdominal pain and diarrhea, with fatigue and no dizziness, no fever, and no cough or sputum.
(7)Patient had sudden chest tightness 8 days ago. He was diagnosed with acute myocardial infarction in a local hospital. After drug treatment, the patient's symptoms did not improve, and he was transferred to the emergency department of our hospital for further diagnosis and treatment, and electrocardiogram was performed in the emergency department, indicating that the ST segment was still elevated.

**Figure 8.** Part of the electronic medical record text diagram.

The dataset was annotated using BIOS sequence labeling. We identified 600 representative electronic medical records and manually annotated them with sequence labels, primarily focusing on chest pain patients with persistent chest pain, intermittent chest pain, resolved chest pain, typical chest pain and atypical chest pain. The corresponding textual data is shown in Figure 8. The text distribution of the electronic medical record is shown in Figure 9 below.

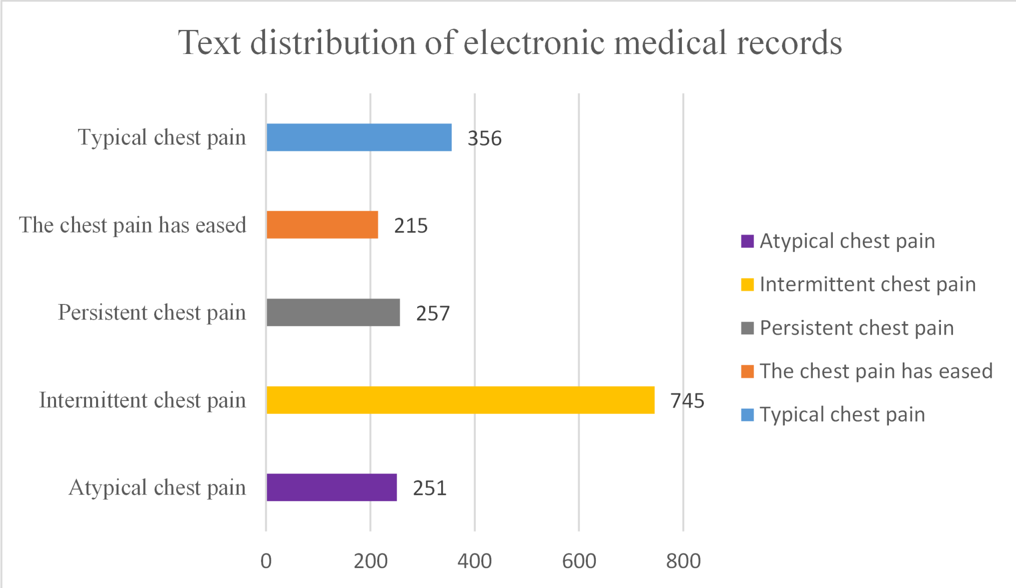


**Figure 9.** Text distribution diagram of electronic medical records.

### *5.2. BILSTM-CRF model*

There are numerous methods available for entity recognition, with one of the popular ones being a combination of the BERT-BiLSTM model structure [24], the BiLSTM-CRF model [25] and self-attention mechanisms [26]. The intelligent chest pain center system employs the BiLSTM-CRF model. BiLSTM is an advanced version based on the long short-term memory network, with "Bi" representing the bi-directional nature of the model. It not only recognizes information that has already occurred but also considers information that will occur in the future to establish context. BiLSTM finds extensive applications in natural language processing, particularly in text classification, named entity recognition and speech recognition. BiLSTM comprises both forward and backward LSTMs, with the forward LSTM processing each element sequentially, while the backward LSTM processes each element in reverse order. Finally, the two modules are utilized to generate the output results.

The BiLSTM maps the input sequence to a series of hidden states, where $h_t$ represents a combination of the state vectors from the forward LSTM and the backward LSTM, as illustrated in the following formulae:

$$\overrightarrow{h_t} = \overrightarrow{LSTM}(\overrightarrow{h_{t-1}}, x_i), \tag{5.1}$$

$$\overleftarrow{h_t} = \overleftarrow{LSTM}(\overleftarrow{h_{t-1}}, x_i), \tag{5.2}$$

where $\overrightarrow{LSTM}$ represents the forward LSTM, $\overleftarrow{LSTM}$ represents the backward LSTM and $x_i$ represents the input sequence. The calculation formula of LSTM is shown in Eqs (5.3)–(5.8):

$$i_t = \alpha(W_i e_t + U_i h_{t-1} + b_i), \tag{5.3}$$

$$f_t = \alpha(W_f e_t + U_f h_{t-1} + b_f), \tag{5.4}$$

$$\tilde{c}_t = \tanh(W\tilde{c}e_t + U_{\tilde{c}} h_{t-1} + b_{\tilde{c}}), \tag{5.5}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t, \tag{5.6}$$

$$o_t = \alpha(W_o e_t + U_o h_{t-1} + b_o), \tag{5.7}$$

$$h_t = o_t \odot \tanh(c_t), \tag{5.8}$$

where $f_t$ represents the weight of forgetting, and $W_f$, $U_f$ and $b_f$ are parameters of the forget gate; $i_t$ represents the weight of input, $\tilde{c}_t$ represents the new information state. $W_i$, $U_i$ and $b_i$ are parameters of the Sigmoid layer in the input gate, and $W_{\tilde{c}}$, $U_{\tilde{c}}$ and $b_{\tilde{c}}$ are parameters of the tanh layer in the input gate; $o_t$ represents the weight of output, and $W_o$, $U_o$ and $b_o$ are parameters of the output gate; $\alpha$ represents the Sigmoid activation function; $\odot$ represents the element-wise product of matrices.

CRF stands for conditional random field. It considers the distribution state of the entire label sequence and predicts the joint probability of the output labels by constraining the joint probabilities of the label sequence. CRF is usually combined with BILSTM to extract label features and calculate the probability of each label sequence using BILSTM. CRF calculates the probability of each label by considering the current label position and the previous label position, thus obtaining the transition probability. The model is then trained to improve this transition probability. The main parameterization formula for CRF is as follows:

$$p(y \mid x) = \frac{1}{Z(x)} \exp\left(\sum_{l,k} \lambda_k t_k(y_{i-1}, y_i, x, i) + \sum_{i,l} \mu_l s_l(y_i, x, i)\right), \tag{5.9}$$

$$Z(x) = \sum\nolimits_y \exp\left(\sum_{l,k} \lambda_k t_k(y_{i-1}, y_i, x, i) + \sum_{i,l} \mu_l s_l(y_i, x, i)\right). \tag{5.10}$$

$t_k$ and $s_l$ are feature functions, where $t_k$ represents a transition feature that depends on the previous item and $s_l$ represents a state feature that depends on the current position. $\lambda_k$ and $\mu_l$ are the corresponding weights.

The model diagram of the BILSTM-CRF algorithm is shown in Figure 10, where "TCP" stands for typical chest pain.

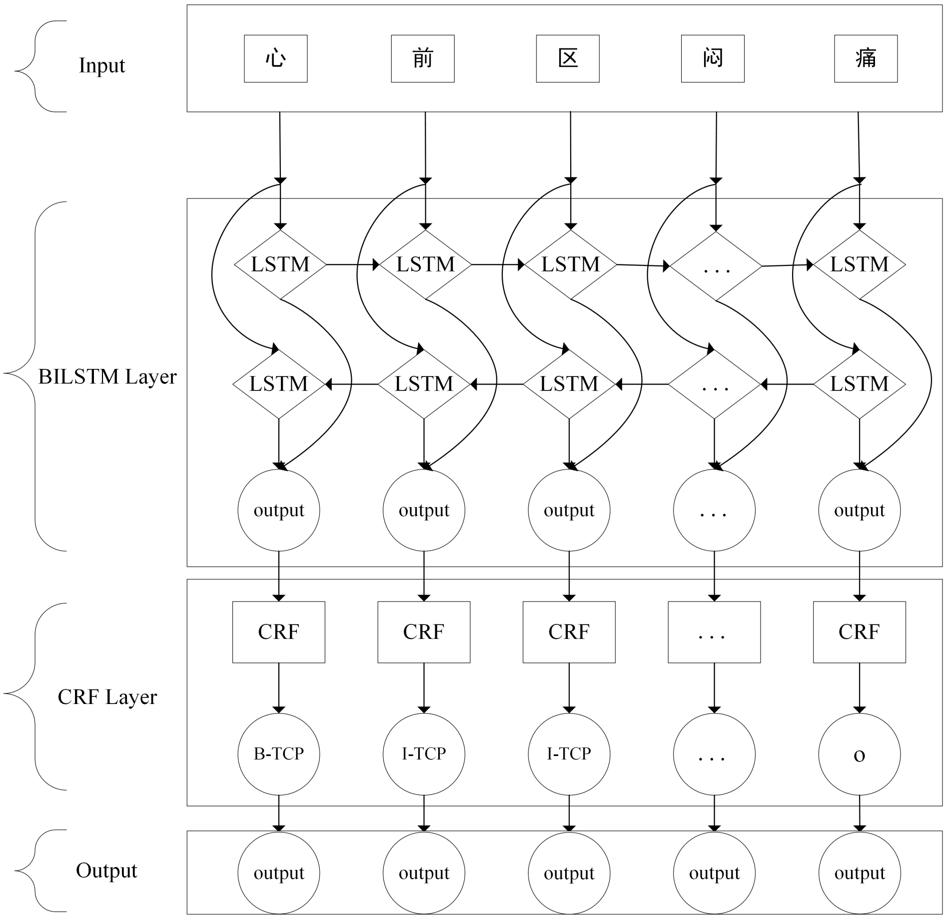


**Figure 10.** BILSTM-CRF model.

## *5.3. Experimental results and analysis*

### 5.3.1. Experimental environment

The experimental environment parameters are shown in Table 3.

**Table 3.** Experimental environment configuration.

| Experimental environment | Parameter information |
|---|---|
| System | Windows 10 |
| CPU | Intel(R) Core(TM) i5-7300HQ CPU @2.50GHz |
| GPU | NVIDIA GeForce GTX 1050 |
| Memory | 16 GB |
| Development language | Python 3.6.2 |
| Development platform | TensorFlow-gpu 1.12.0 |

The primary training parameters of the BiLSTM-CRF model are presented in Table 4.

**Table 4.** Main training parameters of BILSTM-CRF mode.

| Parameter name | Parameter information |
|---|---|
| batch_size | 16 |
| epoch | 40 |
| hidden_dim | 1024 |
| embedding_dim | 1024 |
| lr | 0.001 |
| clip | 5.0 |
| optimizer | Adam |
| dropout | 0.5 |

### 5.3.2. Experimental result

**Table 5.** Distribution of electronic medical record extraction results.

| Tag name | Precision (%) | Recall (%) | F1-score (%) |
|---|---|---|---|
| TCP | 94.44 | 92.73 | 93.58 |
| ACP | 87.80 | 80.00 | 83.72 |
| PCP | 100.00 | 100.00 | 100.00 |
| ICP | 96.06 | 94.12 | 96.83 |
| NoCP | 91.43 | 94.12 | 92.75 |
| **Total** | **94.31** | **93.64** | **93.97** |

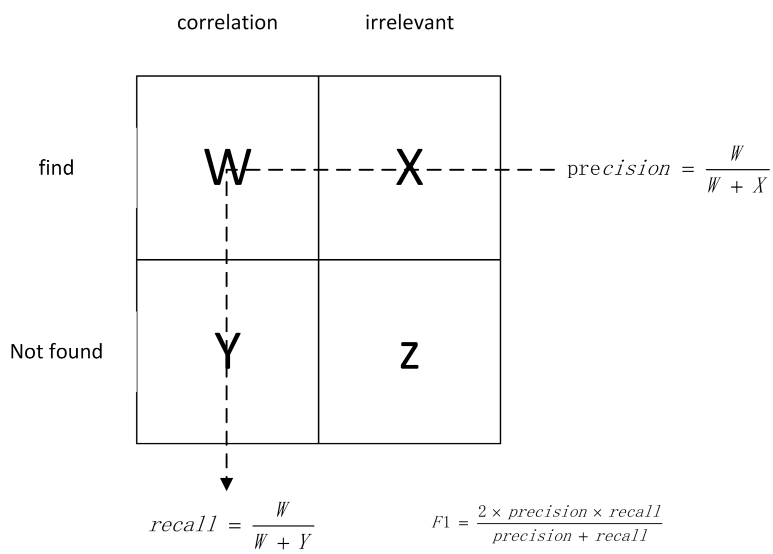


**Figure 11.** Diagram of F1-score.

TCP represents typical chest pain, ACP represents atypical chest pain, PCP represents persistent chest pain, ICP represents intermittent chest pain and NoCP represents relieved chest pain. Total represents the overall label training results. In the Table 5 above, we used precision, recall and F1-score metrics, where the meanings are represented in Figure 11.

In the figure above, precision is calculated by the following formulae:

$$precision = \frac{\text{W}}{\text{W+X}} \times 100\%, \tag{5.11}$$

$$recall = \frac{\text{W}}{\text{W+Y}} \times 100\%, \tag{5.12}$$

where W stands for the number of chest pain electronic medical record texts detected, X stands for the total number of electronic medical records for all chest pain detected and Y stands for the total number of texts of all relevant electronic chest pain medical records. F1-score is as follows:

$$F1 = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision+recall}} \times 100\%. \tag{5.13}$$

By training the algorithm model, the F1 metric reached 93.97%. We also experimented with the BERT-BILSTM-CRF model and the BILSTM model. Among them, the BERT-enhanced BILSTM-CRF model achieved an F1 score of 91.39%, while the BILSTM model without CRF achieved an F1 score of 92.61%. Clearly, the BILSTM-CRF model has a higher F1 score, indicating better performance. Subsequently, symptom information from patient electronic medical records will be extracted and applied to the Smart Chest Pain Center based on certain screening rules to achieve a more accurate screening effect.

### 5.3.3. Experimental analysis

The experiment was conducted using an epoch of 40, which resulted in oscillations when further increased. After multiple trials, 40 was found to have the optimal performance. The extraction rates for atypical chest pain and typical chest pain were relatively low, which could be attributed to the characteristics of the dataset. We conducted a comparative analysis using the BILSTM-CRF, BERT-BILSTM-CRF and BILSTM models. The experimental results are shown in Table 6.

**Table 6.** Comparison of electronic medical record algorithm results.

| Algorithm | Precision (%) | Recall (%) | F1-score (%) |
|---|---|---|---|
| BiLSTM-CRF | 94.31 | 93.64 | 93.97 |
| BERT-BiLSTM-CRF | 90.91 | 91.87 | 91.39 |
| BiLSTM | 92.28 | 92.93 | 92.61 |

To further validate the efficiency of the experiment, different configurations were adopted. The study employed traditional central processing units (CPUs) and graphics processing units (GPUs), with parameters being Intel(R) Core(TM) i5-7300HQ CPU @2.50GHz and NVIDIA GeForce GTX 1050, respectively. In the BILSTM-CRF model, GPU training was nearly seven times faster than CPU training, with specific time complexity comparisons shown in Table 7. In order to better show the effect, we have drawn Figure 12.

**Table 7.** Time complexity comparison.

| Training rounds | CPU time (s) | GPU time (s) |
|---|---|---|
| 5 | 1267 | 176 |
| 10 | 2823 | 397 |
| 20 | 6060 | 819 |
| 30 | 8721 | 1264 |
| 40 | 12,254 | 1711 |

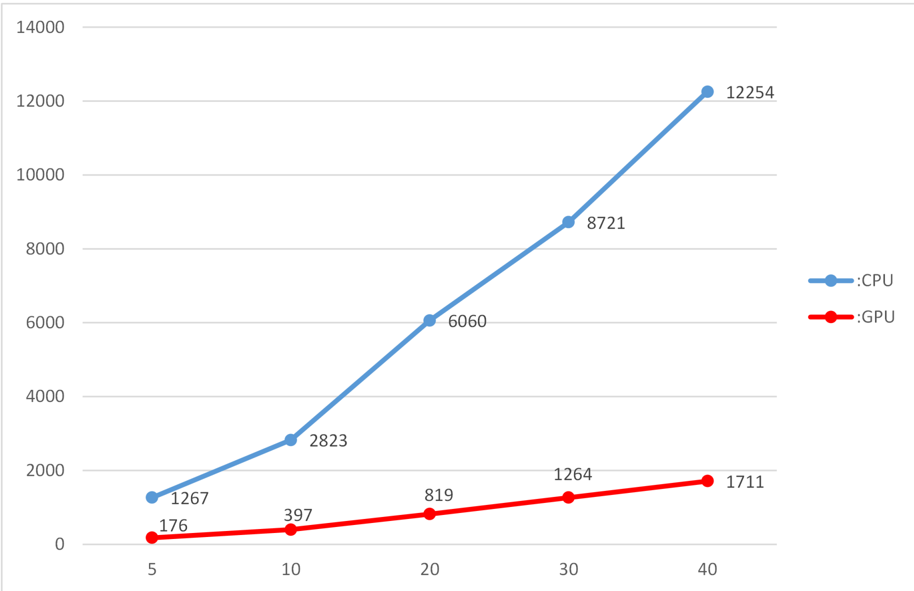


**Figure 12.** Time complexity comparison graph.

We employed the BiLSTM-CRF model to locally extract patients' chest pain symptoms, including persistent chest pain, intermittent chest pain and relieved symptoms. Compared to traditional methods, this optimized approach has shown significant improvement. The time taken for each extraction is only a few hundred milliseconds, greatly enhancing processing efficiency.

## 6. Clinical application

The Smart Chest Pain Center is now in use at Liaoning Provincial People's Hospital. As of now, it has automatically uploaded nearly a thousand cases, with patient diagnoses including UA, STEMI, NSTEMI, pulmonary embolism and aortic dissection. Among them, the automatic transmission of patient electrocardiogram information has reduced the workload of medical staff and facilitated the analysis of patient chest pain symptoms in the future. The system meets the development requirements of chest pain centers, enabling real-time tracking of patient visit data, automatic acquisition of patient basic information, emergency information, chest pain diagnosis and treatment, catheterization room and outcomes, which are connected to the hospital's information system. Compared with traditional manual reporting to the chest pain center, the system improves efficiency and error tolerance. Prior to the application of this system, the hospital relied on manual record-keeping and manual data queries from different systems, which were slow and time-consuming. It took more than half an hour to manually input the data of a STEMI patient, but with this system, the time required has been reduced to a few minutes, and the workload has significantly decreased. At the same time, the system plays an important role in optimizing the workflow of the chest pain center, improving the quality control standards of the chest pain center, increasing the efficiency of the chest pain center and reducing the incidence of acute myocardial infarction in chest pain cases [27, 28]. It also has an auxiliary role in affecting ACS risk assessment [29].

## 7. Discussion

The Internet of Things (IoT) in smart healthcare holds great significance for the advancement of the medical field. Currently, many researchers are exploring its potential. For example, the study conducted by Chen et al. on heart sound analysis [30] is of paramount importance in cardiovascular research. They have also proposed a healthcare IoT-based framework for heart sound collection [31], which greatly contributes to the development and improvement of healthcare. The construction of a Chest Pain Center relies on the support of information technology. This article presents the design of an intelligent Chest Pain Center that can obtain real-time information about patients' treatment in the hospital, including the first electrocardiogram time, the way of arrival and the first medical contact time. It also interfaces with the National Chest Pain Center and supports one-click uploading to the Chest Pain Center reporting system. Compared to the past, which took half an hour to report a single case, the system has achieved "paperless" reporting in a matter of minutes, greatly improving the ability to manage chest pain data.

Due to the complexity and diversity of Chinese electronic medical records, healthcare professionals often invest a significant amount of time manually assessing chest pain results. This paper uses a Chinese electronic medical record entity recognition method, intended for application in medical systems, to significantly enhance the level of intelligence in chest pain center information. Simultaneously, it reduces the time doctors spend processing electronic medical record data, enabling healthcare providers to focus more on patient treatment. The system has been successfully implemented at Liaoning People's Hospital and has received recognition as a nationally distinctive project. Future research directions will further focus on the development of artificial intelligence algorithms to assist healthcare professionals in extracting more electronic medical record text. The extracted data will undergo normalization and be used to analyze whether patients exhibit symptoms of coronary heart disease [32] and similar conditions, ultimately optimizing patient treatment times and achieving more efficient medical services.

## Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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## Conflict of interest

The authors declare there is no conflict of interest.

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