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AI Intelligent Recognition Early Warning System for Steel Mills

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ABSTRACT

The production environment of steel mills is complex, and the equipment is not allowed to stop. The traditional manual monitoring is inefficient, and it is impossible to always monitor data and equipment, which has great security risks. In this paper, an ai intelligent identification and early warning system for steel mills is designed, which integrates two subsystems: safety production early warning and equipment healthy operation early warning, and adopts computer vision (YOLOv5) and time series data analysis (LSTM, self-encoder) technologies respectively to realize workers' behavior monitoring and equipment fault prediction. Through real-time alarm and data visualization, the system can significantly improve the safety and operational efficiency of steel mills.

KEYWORDS

Early Warning System; Steel Mills; Intelligent Recognition; AI

1. INTRODUCTION

The project is commonly used in steel mills and other enterprises and organizations where there are some clear requirements for workers' operation and data processing needs for factory equipment. Through cameras and other equipment, real-time monitoring of specific areas such as workshops, warehouses, construction sites, etc., the use of AI recognition, image recognition and analysis and other technologies to automatically identify abnormalities and unsafe behaviors, and can be linked to the sound and light alarms and other hardware equipment for real-time warnings, and the alarm information is notified to management personnel through the The alarm information is notified to the management personnel through the Web terminal, which protects the safety production of the steel plant. After our visit and investigation, we found that most of today's steel mills use manual monitoring data and video, which is labor-intensive and difficult to achieve real-time monitoring, relying on the experience and level of workers, human error can lead to serious consequences. With the development of artificial intelligence technology, the detection methods are gradually diversified, and the operation principles of blast furnace and other important equipment are gradually clarified. We plan to design the system to have the advantages of wide monitoring range, real-time response, strict accuracy and so on compared with traditional manual monitoring. At the same time equipped with steel plant equipment health warning system, when the steel plant equipment operation process vibration, displacement and other sensor data abnormalities, automatically report to the steel plant management personnel, to attract the attention of the management personnel, instead of manually real-time check the state of operation of the equipment, so as to make the operation of the steel plant equipment is more safe and reliable.

Using advanced machine vision analysis and recognition technology combined with deep learning algorithms, the system conducts real-time monitoring of violations such as illegal operation of heavy vehicles, wearing of helmets and coveralls, intrusion of people in hazardous areas, sleeping away from work, playing with cell phones, smoking, and other violations in steel mills, as well as the working conditions of the staff. The system captures images of the behavior of underground operators through surveillance cameras deployed in key areas and identifies violations through system analysis. Once a violation is detected, the system immediately generates an alarm message and pushes the message to the management center. After receiving the alarm message, the staff in the management center can quickly take measures to stop and deal with the violation, thus effectively avoiding the occurrence of safety accidents.

All in all, the goal of this project is to create a terminal system that can detect factory surveillance video and factory equipment safety in real time.

2. DESIGN IDEAS AND PROGRAMS

Steel plant AI intelligent identification early warning system is divided into two parts: safety production early warning system and equipment health operation early warning system.

2.1. Safety Production Early Warning System

Using advanced machine vision analysis and recognition technology combined with deep learning algorithms, it carries out real-time monitoring of violations such as illegal operation of heavy vehicles, wearing of helmets and overalls, intrusion of people in hazardous areas, sleeping and leaving the post, playing with cell phones, smoking, and other violations in steel mills, as well as the working conditions of the staff. The system captures images of the behavior of underground operators through surveillance cameras deployed in key areas, and identifies violations through system analysis. Once a violation is detected, the system immediately generates an alarm message and pushes the message to the management center. After receiving the alarm message, the staff in the management center can take prompt measures to stop and deal with the violation, thus effectively avoiding the occurrence of safety accidents.

(1) Training model:

According to the real surveillance video material we got from the steel mill, we get the needed model material by randomly taking frames, and use labelImg to label the images, use YOLOV5 to train the Pytorch model, and then convert it to the trt model of TensorRT by ONNX to optimize the model to improve the efficiency.

(2) Dangerous area detection is partly judged by boxing the dangerous area and using the position between the worker and the dangerous area.

(3) The design idea of off-duty detection is to divide the video frame into nine regions, according to the provisions of the steel plant employee code (important areas of the steel plant central control room need to be on duty 24 hours a day, and the number of people in the central control room should not be less than 5), by judging the region where the recognition target is located, and the number of regions where the recognition target exists to determine, whether the central control room is in line with the steel plant's mandatory regulations.

(4) Fatigue detection is the use of recognition of the 68 key points of the face, the detection of the eyes and mouth of the aspect ratio to determine the action of closing the eyes and opening the mouth, through the number of consecutive frames of closing the eyes or opening the mouth to determine the "yawn" and "sleep" behavior.

(5) The detection part of the code is completed, it will be loaded into the Flask framework, so that it is deployed on the Web side of the detection video and alarm information into the front-end and displayed on the browser page.

2.2. Equipment Health Diagnosis and Early Warning System

Stable operation of equipment and safe operation of personnel are crucial in the production process of steel mills. For this reason, an intelligent data analysis and prediction alert system is designed to monitor and predict the operating status of equipment in steel mills in real time through advanced machine learning algorithms and deep learning models. The system collects and analyzes sensor data to accurately predict the risk of equipment failure and identify anomalies in the production process in real time. Once an anomaly or potential failure is detected, the system immediately generates an alert message and pushes the information to the management center. Upon receiving the alert message, staff at the management center can take prompt action to avoid production accidents and improve the overall operational efficiency of the steel plant.

(1) Sensor data collection

Deploy sensors in the key monitoring equipment in the steel plant, real-time data collection and data preprocessing and transmission through NIFI and kafka, deployed in the influxdb time series database to ensure efficient data collection.

(2) Data analysis and fault prediction

The lstm model trained with real steel plant data is used for real-time data prediction, identifying abnormal trends and potential risks in the operation of the equipment, and using the self-encoder model to create an alarm system, which has a lower false alarm rate and the ability to dynamically set the alarm threshold compared to simple threshold alarms, and adapts to a wider range of different sensors.

(3) Abnormality detection and alarm

The system combines the prediction results of the lstm model and the results of the autoencoder model to return alarm data to the front-end, and visualize and alert the front-end for the error data, so that the user can better identify the data problem.

(4) Management center response

After an alarm occurs, the staff can view the detailed abnormality and equipment operation data visualization through the interface, record the processing and cause of the alarm to form a traceable operation and maintenance files, and at the same time, allow the customer to write the solution and the cause of the error for the design of the training of the classification and natural language processing models to assist the staff to locate the problem.

(5) Data visualization and monitoring interface

The advanced data visualization solution, ECharts, is used to build a large data screen, making the data more readable and analyzable, and helping workers identify potential problems and optimization possibilities in the production process.

3. PROGRAMMATIC REALIZATIONS

3.1. Project Overview

Project Background: Steel plant production environment is complex, there are high temperature, dust and noise and other unfavorable factors, the traditional manual monitoring and identification methods are inefficient, and there are security risks. Through the AI intelligent recognition system, it can realize real-time monitoring and analysis of the production environment, equipment operation, worker safety and other aspects.

Project Objective: Utilize computer vision, machine learning and deep learning technology to realize real-time monitoring and identification of key nodes and safety risks in the production process of steel mills, improve production efficiency and reduce the incidence of safety accidents.

3.2. System Functions

Real-time monitoring: Real-time monitoring of production lines, equipment, workers' behavior, etc. using cameras and sensors.

Safety Recognition: Automatically recognizes whether workers are wearing safety equipment, whether they are staying in dangerous areas, and whether equipment is malfunctioning.

Alarm system: Automatically sends out alarms and pushes them to the terminals of relevant personnel in response to recognized abnormal situations.

Data analysis: Analyze historical data through data visualization, predict potential safety hazards, and issue timely alarms to reduce the pressure on the central control room.

3.3. Technical Programs

3.3.1. Hardware Technology

Camera: Industrial-grade HD camera, adapting to high temperature and dusty environment, supporting night vision function.

Computing device: Industrial computer equipped with high-performance GPU for model inference and data processing.

Sensors: Temperature, smoke, vibration and other sensors for monitoring the environment and equipment status.

3.3.2. Software Technology

Computer Vision

Computer vision technology is an important branch of computer science, which enables machines to "see" and understand visual information, and analyze visual data through algorithms and models to extract meaningful features and information by simulating the human visual system. In this system, it is mainly used to monitor the behavior of workers and the status of factory equipment. [1] The core components include:

Object Detection (Object Detection): YOLOv5 (You Only Look Once) model is used for real-time detection of whether workers are wearing helmets, intrusion in dangerous areas, and workers leaving the workplace, etc. The YOLO series models are highly adaptable in industrial scenarios due to their high speed and high accuracy. [2]

Behavioral Analysis (Action Recognition): Analyze the posture and behavior of workers through key point detection (e.g., OpenPose) to identify violations such as smoking, sleeping on duty, and fatigue. [3]

Face Recognition (Face Recognition): use ResNet or MobileFaceNet to detect the identity of the worker and combine it with a fatigue detection model (based on eye closure time) to recognize whether the worker is in a fatigue state.

Long Short-Term Memory Network (LSTM, Long Short-Term Memory)

LSTM is a type of recurrent neural network (RNN) for processing time-series data, capable of learning long-term dependencies of data. Compared with ordinary recurrent neural networks, LSTM adds three gate structures of forgetting gate input gate and output gate internally, and this design can effectively capture the long-term dependencies of data and alleviate the problems of gradient vanishing and gradient explosion.[4]

In this system, LSTM is used:

Predictive Maintenance (Predictive Maintenance): Analyze sensor data (e.g., temperature, vibration, pressure) and predict future equipment data to detect anomalous trends in advance and reduce losses due to sudden failures.

Anomaly Detection (Anomaly Detection): By learning the normal equipment operation mode, once the sensor data deviates from the normal mode, LSTM can mark it as anomaly and trigger an alarm.

Convolutional Neural Networks (CNN, Convolutional Neural Networks)

Convolutional Neural Networks (Convolutional Neural Networks), widely used in image and video analysis, are deep learning models or multilayer perceptrons similar to artificial neural networks that are commonly used to analyze visual images. [5]

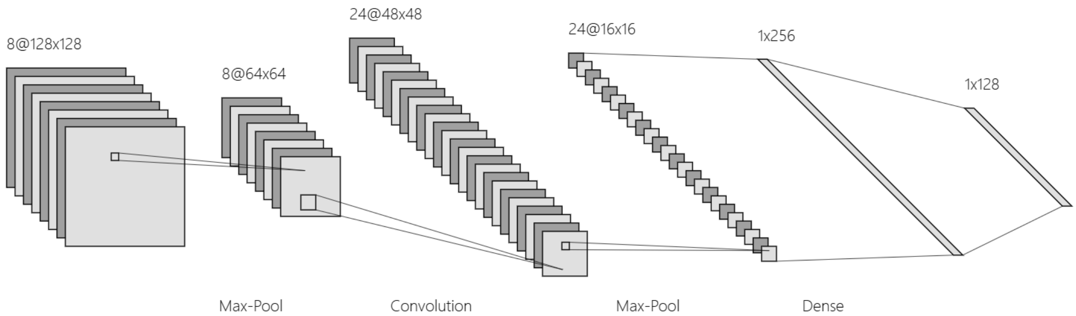

Figure 1. Convolutional Neural Networks

The structure of a convolutional neural network is shown in the figure above, a convolutional neural network is mainly composed of a data input layer, a convolutional computation layer, a RELU excitation layer, a pooling layer and a fully connected layer, the data input layer is responsible for preprocessing the data including de-mean, normalization and whitening, etc., the convolutional computation layer introduces nonlinearity by convolving the input image with a convolutional kernel, and then with an activation function (e.g., ReLU). The most important role of pooling layer is to compress the image and reduce overfitting.

It is mainly used in this system:

Video surveillance analysis: target detection of factory surveillance video to identify workers, machinery and equipment and dangerous areas. Prevent workers from entering hazardous areas rashly.

Environmental state detection: Identify dangerous situations such as smoke and sparks in the steel plant workshop through image analysis, and warn in advance. Avoid staff monitoring can not detect the problem.

Autoencoder (Autoencoder)

Autoencoder is an unsupervised learning model mainly used for anomaly detection. In this system, the main applications of autoencoder include:

Device health status monitoring: learning the normal operation mode of the device and triggering an anomaly alarm once a data point deviating from the normal mode is detected.

Dynamic threshold setting: Different devices have different abnormal ranges, and traditional threshold alarms are prone to false alarms. Self-encoder is able to adaptively set the abnormality threshold by learning the operation mode of different devices, which reduces the false alarm rate.

3.4. System Integration

Hardware Integration: Connect cameras, sensors, and computing devices to the central server through the network to build the Industrial Internet of Things (IIoT) architecture.

Software Integration: Integrate video stream processing, target detection, alarm push and other functional modules to form a complete monitoring and identification system.

3.5. Expected Results

Improvement of production safety: Real-time monitoring of workers and equipment status, timely detection and treatment of potential safety hazards.

Efficiency Improvement: Automated monitoring and identification, reducing manual intervention and improving production efficiency.

Data-driven decision-making: Optimize production processes and reduce costs based on analysis and prediction of historical data.

4. RUNNING RESULTS/APPLICATION EFFECTS

Practical effect demonstration:

Safety production early warning system:

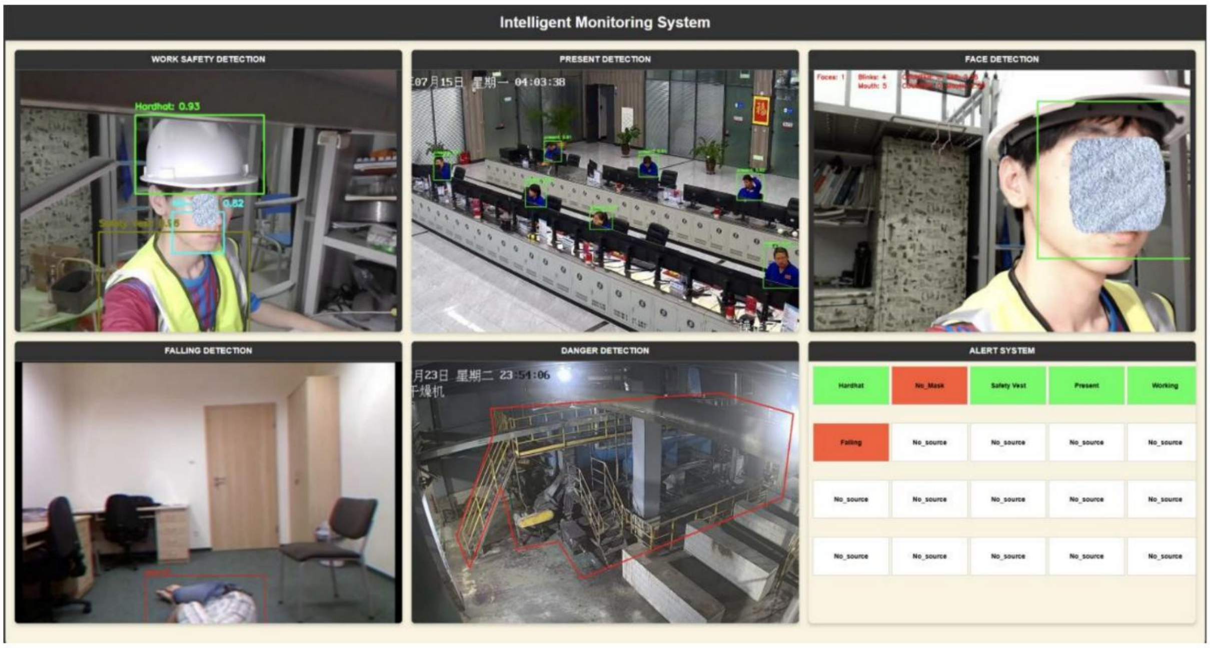

Figure 2. Safety production early warning system

The first five in the page design are worker safety detection, off-duty detection, face fatigue detection, fall detection, and dangerous area detection. The last module is the alarm information module, the back-end through Flask comes with the jsonify module to return the json data and the detection results will be summarized and displayed in the alarm module.

Equipment health operation warning system:

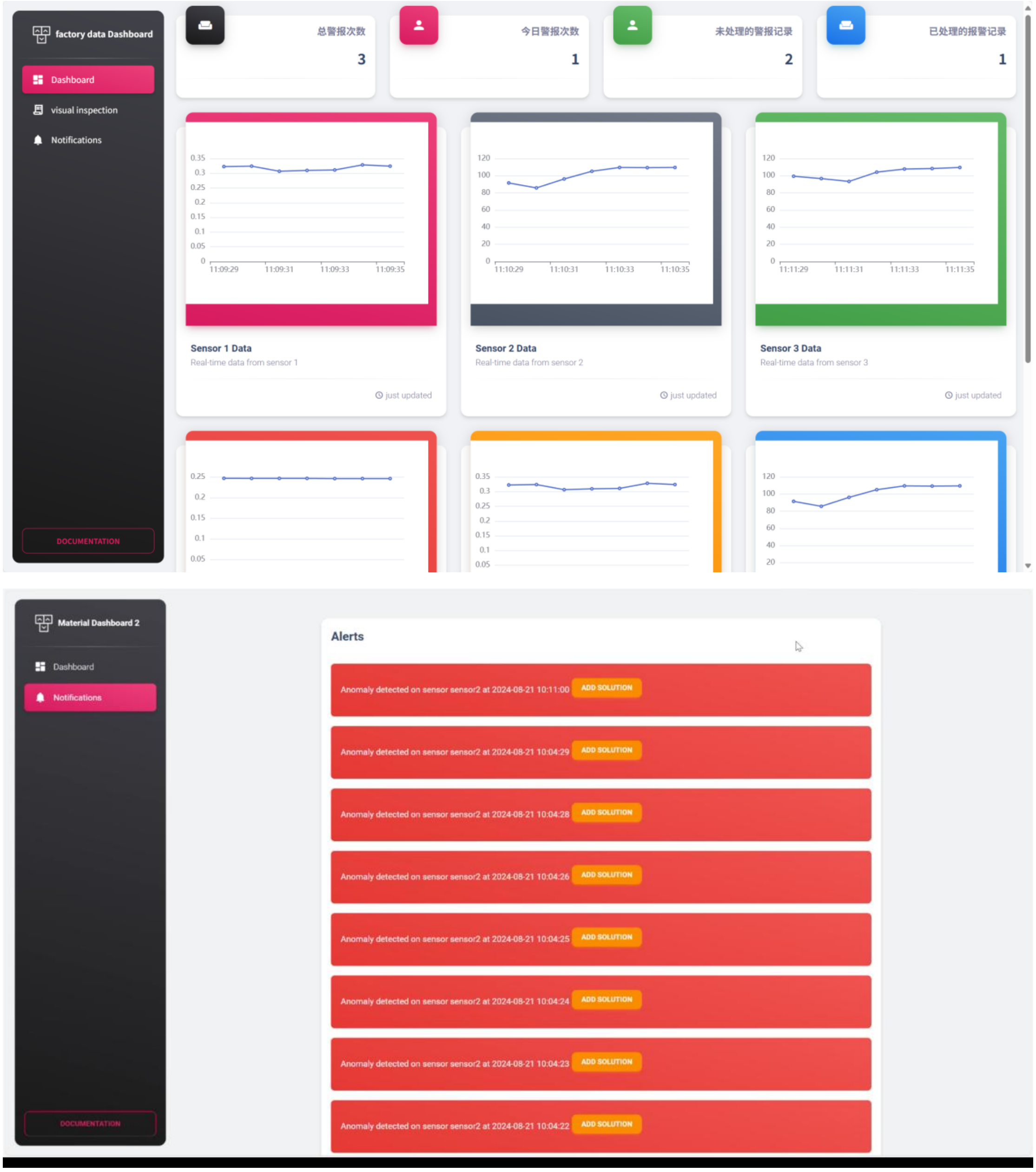

Figure 3. Equipment health operation warning system

Data visualization and alert logging on the web side, real-time updating and aggregation of data, and display of error data logging in Notifications.

Reflection and Analysis

During the development of the project, the author realized that lstm is still insufficient for the long time series data of steel enterprises, and the reason is attributed to the fact that the current way of handling the data in steel mills is still in the stage of manual processing, which does not form a complete chain of data, and is unable to correspond the anomalies with the original data, and at the same time there is inevitably the presence of noise. A variety of environmental factors will have a direct impact on the steel mill data, such as the huge temperature difference caused by the season, which makes the self-coder report more anomalies. In the subsequent research and improvement, in order to overcome the limitations of LSTM and selfencoder in steel mill data processing, the following optimization strategies are planned:

Fusion of Transformer architecture: replacing the traditional LSTM to improve the time-series data modeling capability, e.g., adopting the Transformer-based Time-Series Forecasting (TFT) model.

Edge Computing Optimization: deploy lightweight models (e.g., Mobile Net, Tiny-YOLO) in industrial environments to reduce computational costs and improve real-time performance.

Adaptive anomaly detection: introduce adversarial training or Bayesian self-encoder to reduce the false alarm rate and improve the generalization ability of anomaly detection.

5. INNOVATIONS AND FEATURES

Nowadays, the monitoring system and safety supervision in steel mills rely entirely on manual operation, which on the one hand consumes a lot of manpower, and on the other hand can't avoid staff fatigue and the occurrence of various emergencies. This project steel plant AI intelligent identification early warning system using real scenes related to video and equipment data, the relevant requirements from the actual scene of the steel plant, the field visit will be related to the needs of the collation, and the use of artificial intelligence technology to solve the problem, through the project can reduce the safety accidents in steel mills, and optimize the process of equipment management in steel mills.

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