Deep Learning
 Deep Learning

Xiaoqing Yu, Hongen Wu, Hu Cui, Yongding Xie, Yongqua
 Abstract—The connecting buckles of underground
 Abstract—The connecting buckles of underground
 Abstract—The connecting buckles of Connecting Buckles

ansportation Belts with

carning

ding Xie, Yongquan Wang, Xiliang Ma

confined compared to ground-level operations (see Fig. 1(b)).

Traditional vulcanized splicing is greatly restricted, and this
 IAENG International Journal of Computer Science

Defect Detection Study of Connecting Buckles

for Mining Powerful Transportation Belts with

Deep Learning

Xiaoqing Yu, Hongen Wu, Hu Cui, Yongding Xie, Yongquan Wang, Xili IAENG International Journal of Computer Science

Defect Detection Study of Connecting Buckles

for Mining Powerful Transportation Belts with

Deep Learning

Xiaoqing Yu, Hongen Wu, Hu Cui, Yongding Xie, Yongquan Wang, Xili Experiment

In Study of Connecting Buckles

erful Transportation Belts with

Deep Learning

Vu, Hu Cui, Yongding Xie, Yongquan Wang, Xiliang Ma

Vu, Hu Cui, Yongding Xie, Yongquan Wang, Xiliang Ma

confined compared to gro Ct Detection Study of Connecting Buckles

Tining Powerful Transportation Belts with

Deep Learning

Xiaoqing Yu, Hongen Wu, Hu Cui, Yongding Xie, Yongquan Wang, Xiliang Ma

confined compared to ground-level operations (see

the Community of the U.S. Examplement Community Community

Xiaoqing Yu, Hongen Wu, Hu Cui, Yongding Xie, Yongquan Warract—The connecting buckles of underground raditional vulcanized sp

transportation belts are a critica **COP Learning**

Xiaoqing Yu, Hongen Wu, Hu Cui, Yongding Xie, Yongquan W

confined compared to graditional vulcanized s
 Abstract—The connecting buckles of underground

transportation belts are a critical components are **EXECUTE COLUMBERT SET ASSETT AND CONTROLLER SET ASSETT AND CONTROLLER CONTROLL** Xiaoqing Yu, Hongen Wu, Hu Cui, Yongding Xie, Yongquan Wan₂
 *Abstract***—The connecting buckles of underground** Traditional vulcanized splice
 confined compared to groum
 confined compared to groum
 confined co Xiaoqing Yu, Hongen Wu, Hu Cui, Yongding Xie, Yongquan Wang

confined compared to ground
 Abstract—The connecting buckles of underground

Traditional vulcanized splicin

transportation belts are a critical component. The Xiaoqing Yu, Hongen Wu, Hu Cui, Yongding Xie, Yongquan Wan,

confined compared to groum
 Abstract—The connecting buckles of underground Traditional vulcanized splice

transportation belts are a critical component. These
 Xiaoqing Yu, Hongen Wu, Hu Cui, Yongding Xie, Yongquan W

confined compared to gro
 confined compared to gro
 confined compared to gro
 crasportation belts are a critical component. These

components are use
 *curren dbstract***—The connecting buckles of underground Traditional vulcanized transportation belts are a critical component. These components are susceptible to damage from material impact For frequently movies and pulley wear**mostract—The connecting buckles of underground Traditional vulcanized splicity transportation belts are a critical component. These components are susceptible to damage from material impact For frequently moving we and pul **abstract—The connecting buckles of underground** Traditional vulcanized is
 atternal components are useeptible to damage from material impact

and pulley wear-induced damage, which can compromise

and pulley wear-induced **Examplementation** betts are a critical component. The connection vertical components are a critical component. These and pulley wear-induced damage from material impact For frequently moving and pulley wear-induced damage *Abstract*—The connecting buckles of underground method is only en
transportation belts are a critical component. These
components are susceptible to damage from material impact
and pulley wear-induced damage, which can co **validation** belts the connection belts are a critical component. These frame end pulley wear-induced damage from material impact and pulley wear-induced damage, which can compromise incensions, the conveyor belt importanc **Examplemental and an area are the components are susceptible to damage from material impact

and pulley wear-induced damage, which can compromise

industrial safety and transportation efficiency. While the reassembled fre** components are susceptione to uainage roun inacterial minipalse
and pulley wear-induced damage, which can compromise occasions, the conveyor belt
industrial safety and transportation efficiency. While the reassembled frequ and purely wear-inuoused uamage, wince an empirominant purely wear-inuoused and the entire onveyor belt to the entire conveyor belt to the entire convert dataset of detection method sing an enhanced version of the YOLOv7 m **Example 12** and transportation enterting. The the entertion enterting backles have gradually self-evident, effective methods to solve this problem are However, damage to teurrently lacking. To fill this gap, this study pr myoriane or uncerceiving useress in connecting buckets is buckets interest in the currently lacking. To fill this gap, this study proposed a defect entire conveyor belt to tedetection method using an enhanced version of th **Exercise throw the mendos of solve the search provides a valuable reference for** the provident and a set and detection methanism, and a loss function of the YOLOv7 system failure fig. Therefore model. The process incorpor Extremely incoming To in this gap, this study proposed a tercet
detection method using an enhanced version of the YOLOv7
model. The process incorporated a target detection head, an
generalization ability and robustness und detection method using an emianced version of t
model. The process incorporated a target detecti
attention mechanism, and a loss function to enhance
generalization ability and robustness under comp
environments and diverse **EXERIBITHING THE CHATE AND SOLUTED THE CHANGE THE CHANGE THE CHANGE THE CHANGE OF COLUTION**
 INTERNATION AND CONSTRUCTED IN ONE CONFIDENTIFY
 IITER CONSTRUCTED IN SECT. THE CONFIDENCIAL SECTION
 ITERNATION: The enha generalization abiny and robustness under complex
environments and diverse defect types. Through experalidation using a self-constructed U38 buckle data
method achieved an 83.2% detection rate for various
types, with criti iverse defect types. Through experimental Defect def-

aller the self-constructed U38 buckle dataset, the

nanual de

lefects identified with an accuracy of up to

ced YOLOv7_m model exhibited strong

cert detection, provi

Index Terms—Deep learning; Defect detection; Connecting

exhibit superion

exhibit superion

exhibit superion

approaches. T

I. INTRODUCTION Neural Networ

reproaches. The powerful belt conveyor (see Fig. 1(a)) is widel I. INTRODUCTION

The powerful belt conveyor (see Fig. 1(a)) is wide

for bulk material transportation in mining systems

plays a crucial role [2]. It relies on connection devices

various components. The operating space i

for bulk material transportation in mining systems [1] and
plays a crucial role [2]. It relies on connection devices to link
various components. The operating space in the mine is more
Manuscript received May 2, 2024; revi Various Components. The operating space in the initie 1
Manuscript received May 2, 2024; revised September 25, 2024.
Hongen Wu is an associate professor of College of Mechan
Electronic Engineering, Shandong University of S Manuscript received May 2, 2024; revised September 25, 2024.

Hongen Wu is an associate professor of College of Mechanical and

Electronic Engineering, Shandong University of Science and Technology,

Qingdao 266590, SD, Ch

Umgdao 266590, SD, China (corresponding author, phone: $+86+13969603895$; e-mail: whenli@sina.com)

Electronic Engineering, Shandong University of Science and Technology,

Qingdao 266590, SD, China. (e-mail: 1468915885@qq.

Electronic Engineering, Shandong University of Science and Technology,

Hin Cui is a postgraduate student of College of Mechanical and Electronic

Hu Cui is a postgraduate student of College of Mechanical and Electronic

2

EXECUTE SOFTING SURVERTS
 EXECUTE:
 E and is only and in the Secure 19.15 With
 and ing Xie, Yongquan Wang, Xiliang Ma
 confined compared to ground-level operations (see Fig. 1(b)).

Traditional vulcanized splicing is greatly restricted, and this

method **EXECT ACTION DURIS WILLI
FORMING**
For Form Salison Wang, Xiliang Ma
confined compared to ground-level operations (see Fig. 1(b)).
Traditional vulcanized splicing is greatly restricted, and this
method is only employed in **Carning**

ding Xie, Yongquan Wang, Xiliang Ma

confined compared to ground-level operations (see Fig. 1(b)).

Traditional vulcanized splicing is greatly restricted, and this

method is only employed in fixed transportatio **EXTIMPS**

ding Xie, Yongquan Wang, Xiliang Ma

confined compared to ground-level operations (see Fig. 1(b)).

Traditional vulcanized splicing is greatly restricted, and this

method is only employed in fixed transportatio ding Xie, Yongquan Wang, Xiliang Ma

confined compared to ground-level operations (see Fig. 1(b)).

Traditional vulcanized splicing is greatly restricted, and this

method is only employed in fixed transportation scenarios ding Xie, Yongquan Wang, Xiliang Ma
confined compared to ground-level operations (see Fig. 1(b)).
Traditional vulcanized splicing is greatly restricted, and this
method is only employed in fixed transportation scenarios.
F ding Xie, Yongquan Wang, Xiliang Ma

confined compared to ground-level operations (see Fig. 1(b)).

Traditional vulcanized splicing is greatly restricted, and this

method is only employed in fixed transportation scenarios ding Xie, Yongquan Wang, Xiliang Ma

confined compared to ground-level operations (see Fig. 1(b)).

Traditional vulcanized splicing is greatly restricted, and this

method is only employed in fixed transportation scenarios confined compared to ground-level operations (see Fig. 1(b)).
Traditional vulcanized splicing is greatly restricted, and this
method is only employed in fixed transportation scenarios.
For frequently moving working surfac confined compared to ground-level operations (see I
Traditional vulcanized splicing is greatly restricted
method is only employed in fixed transportation s
For frequently moving working surfaces and
occasions, the conveyor nfined compared to ground-level operations (see Fig. 1(b)).
aditional vulcanized splicing is greatly restricted, and this
thod is only employed in fixed transportation scenarios.
r frequently moving working surfaces and ch Traditional vulcanized splicing is greatly restricted, and this
method is only employed in fixed transportation scenarios.
For frequently moving working surfaces and changing
occasions, the conveyor belt needs to be disass method is only employed in fixed transportation scenarios.
For frequently moving working surfaces and changing
occasions, the conveyor belt needs to be disassembled and
reassembled frequently, and the conveyor belt connect For frequently moving working surfaces and changing
occasions, the conveyor belt needs to be disassembled and
reassembled frequently, and the conveyor belt connecting
buckles have gradually become the main connecting devic

The powerful belt conveyor (see Fig. 1(a)) is widely used requirements. Since then,

The powerful refuge of DLOV⁷__m model exhibited at the ender to the e types, with critical defects identified with an accuracy of up to

198.1%. The enhanced YOLOV⁷ m model exhibited strong to touch and visual inspection. No

198.1%. The enhanced YOLOV⁷ m model exhibited strong only tra 98.1%. The enhanced YOLOv7_m model exhibited strong

performance in defect detection, providing valuable technical offer high accuracy and real-ti

support for improving the safety and efficiency of coal mine

sure transp performance in defect detection, providing valuable technical
support for improviding convert framesportation. This research provides a valuable reference for
transportation. This research provides a valuable reference for Exhibit superior accuracy

Exhibit superior accuracy

Exhibit superior accuracy

I. INTRODUCTION Neural Networks) [6]

The powerful belt conveyor (see Fig. 1(a)) is widely used

Fully material transportation in mining syst Electronic Engineering, Shandong University of Science and Technology,
Electronic Engineering, Blandong University of Science and Technology,
Electronic Engineering, Shandong University of Science and Technology,
Electroni I. INTRODUCTION

The powerful belt conveyor (see Fig. 1(a)) is widely used

for bulk material transportation in mining systems [1] and

plays a crucial role [2]. It relies on connection devices to link

various components. The powerful belt conveyor (see Fig. 1(a)) is widely used

relative that applies

relative to the Mechanical transportation in mining systems [1] and

trious components. The operating space in the mine is more

requirement The powertul belt conveyor (see Fig. 1(a)) is widely used

for bulk material transportation in mining systems [1] and

plays a crucial role [2]. It relies on connection devices to link

various components. The operating sp is a crucial role [2]. It relies on connection devices to link

rious components. The operating space in the mine is more

models, including S

CenterNet [8], and

Manuscript received May 2, 2024; revised September 25, 202 requirements. Since

various components. The operating space in the mine is more

models, including SS

Manuscript received May 2, 2024; revised September 25, 2024.

Hongen Wu is an associate professor of College of Mechan CenterNet [8], and YOL

Hongen Wu is an associate professor of College of Mechanical and

detection efficiency of

teronic Engineering, Shandong University of Science and Technology,

1960-266590, SD, China (orresponding a Manuscript received May 2, 2024; revised September 25, 2024.

Electronic Engineering, Shandong University of Science and Technology,

Electronic Engineering, Shandong University of Science and Technology,

Qingdao 266590, Hongen Wu is an associate protessor of College of Mechanical and

etection efficiency of

engdao 266590, SD, China (orresponding author, phone:

5+13969603895; e-mail: whenli@sina.com)

Xiaoqing Yu is a postgraduate studen Electronic Engineering, Shandong University of Science and Technology, model must balan (intersection) and the setter suited to 266590 , SD, China. (e-mail: 1468915885@q.com) Hu Cui is a postgraduate student of College of A interest and the multiple student of College of Mechanical and Tell in proposed an enhable student of College of Mechanical and Electronic Engineering, Shandong University of Science and Technology, defect identification Xiaoqing Yu is a postgraduate student of College of Mechanical and

Electronic Engineering, Shandong University of Science and Technology,

Clingdao 266590, SD, China. (e-mail: 1468915885@qq.com)

Hu Cui is a postgraduate occasions, the conveyor belt needs to be disassembled and
reassembled frequently, and the conveyor belt connecting
buckles have gradually become the main connecting devices.
However, damage to the connecting buckles may ca reassembled frequently, and the conveyor belt connecting
buckles have gradually become the main connecting devices.
However, damage to the connecting buckles may cause the
entire conveyor belt to tear and disconnect, or ev buckles have gradually become the main connecting devices.
However, damage to the connecting buckles may cause the entire conveyor belt to tear and disconnect, or even lead to system failure [3]. Therefore, the detection a However, damage to the connecting buckles may cause the entire conveyor belt to tear and disconnect, or even lead to system failure [3]. Therefore, the detection and maintenance of the connecting buckles are crucial for th entire conveyor belt to tear and disconnect, or even lead to
system failure [3]. Therefore, the detection and maintenance
of the connecting buckles are crucial for the normal operation
of coal mine production.
Defect detec system failure [3]. Therefore, the detection and maintenance
of the connecting buckles are crucial for the normal operation
of coal mine production.
Defect detection methods can be broadly categorized into
manual detection of the connecting buckles are crucial for the normal operation
of coal mine production.
Defect detection methods can be broadly categorized into
manual detection methods [4] and non-destructive testing
methods [5]. Manual of coal mine production.

Defect detection methods can be broadly categorized into

manual detection methods [4] and non-destructive testing

methods [5]. Manual detection primarily relies on human

touch and visual inspec Defect detection methods can be broadly categorized into
manual detection methods [4] and non-destructive testing
methods [5]. Manual detection primarily relies on human
touch and visual inspection. Non-destructive testing manual detection methods [4] and non-destructive testing
methods [5]. Manual detection primarily relies on human
touch and visual inspection. Non-destructive testing methods
offer high accuracy and real-time capabilities, methods [5]. Manual detection primarily relies on human
touch and visual inspection. Non-destructive testing methods
offer high accuracy and real-time capabilities, making them
crucial for preventing conveyor belt tearing touch and visual inspection. Non-destructive testing methods
offer high accuracy and real-time capabilities, making them
crucial for preventing conveyor belt tearing and enabling
real-time monitoring. Machine vision method offer high accuracy and real-time capabilities, making them
crucial for preventing conveyor belt tearing and enabling
real-time monitoring. Machine vision methods are the
predominant technology in this field. Detecting da crucial for preventing conveyor belt tearing and enabling
real-time monitoring. Machine vision methods are the
predominant technology in this field. Detecting damage to
buckles is essentially a matter of target detection. real-time monitoring. Machine vision methods are the predominant technology in this field. Detecting damage to buckles is essentially a matter of target detection. In particular, deep learning-based target detection metho predominant technology in this field. Detecting damage to buckles is essentially a matter of target detection. In particular, deep learning-based target detection methods exhibit superior accuracy and speed compared to tr buckles is essentially a matter of target detection. In particular, deep learning-based target detection methods exhibit superior accuracy and speed compared to traditional approaches. The R-CNNs (Region-based Convolution particular, deep learning-based target detection methods
exhibit superior accuracy and speed compared to traditional
approaches. The R-CNNs (Region-based Convolutional
Neural Networks) [6] algorithm is a pioneering networ exhibit superior accuracy and speed compared to traditional
approaches. The R-CNNs (Region-based Convolutional
Neural Networks) [6] algorithm is a pioneering network
architecture that applies deep learning to target detect approaches. The R-CNNs (Region-based Convolutional
Neural Networks) [6] algorithm is a pioneering network
architecture that applies deep learning to target detection.
However, this algorithm suffers from a large number of Neural Networks) [6] algorithm is a pioneering network
architecture that applies deep learning to target detection.
However, this algorithm suffers from a large number of
candidate frames, making it challenging to meet re architecture that applies deep learning to target detection.
However, this algorithm suffers from a large number of
candidate frames, making it challenging to meet real-time
requirements. Since then, single-stage target d However, this algorithm suffers from a large number of candidate frames, making it challenging to meet real-time requirements. Since then, single-stage target detection models, including SSD (Single Shot MultiBox Detector candidate frames, making it challenging to meet real-time
requirements. Since then, single-stage target detection
models, including SSD (Single Shot MultiBox Detector) [7],
CenterNet [8], and YOLO (You Only Look Once) [9] requirements. Since then, single-stage target detection models, including SSD (Single Shot MultiBox Detector) [7], CenterNet [8], and YOLO (You Only Look Once) [9], have been introduced. Given the belt speed $(\geq 1.5m/s)$, models, including SSD (Single Shot MultiBox Detector) [7],
CenterNet [8], and YOLO (You Only Look Once) [9], have
been introduced. Given the belt speed (\geq 1.5m/s), and the
detection efficiency of the end device [10], t CenterNet [8], and YOLO (You Only Look Once) [9], have
been introduced. Given the belt speed (\geq 1.5m/s), and the
detection efficiency of the end device [10], the detection
model must balance accuracy and speed. Singlebeen introduced. Given the belt speed (\geq 1.5m/s), and the detection efficiency of the end device [10], the detection model must balance accuracy and speed. Single-stage models are better suited to meet this requirement detection efficiency of the end device [10], the detection
model must balance accuracy and speed. Single-stage models
are better suited to meet this requirement. M. Y. Chen et al.
[11] proposed an enhanced YOLOv4-tiny algo model must balance accuracy and speed. Single-
are better suited to meet this requirement. M. Y
[11] proposed an enhanced YOLOv4-tiny a
defect identification on conveyor belts. They
image segmentation techniques to accurat

mine

From on-site shooting, but the requires a large amount of date

(a) The powerful belt conveyor (b) The operating space in the expanded [18]. After the expanded [18]. After the expanded [18]. After the expanded [18]. After requires a large amount of data

(a) The powerful belt conveyor

(b) The operating space in the

the data enhancement effects so here the original im

expanded [18]. After the expans

frig. 1. The mining conveyor.

The mai defects, so here the original images

(a) The powerful belt conveyor

Fig. 1. The mining conveyor.

Fig. 1. The mining conveyor.

Fig. 1. The mining conveyor.

The main contributions of this paper are as follows: (1) A

im expanded [18]. After the powerful belt conveyor

Fig. 1. The mining conveyor.

Fig. 1. The mining conveyor.

images, the specific ty

dependence in the data enhancement

fig. 1. The main contributions of this paper are as (a) The powerful belt conveyor (b) The operating space in the the data enhancement effects a

Fig. 1. The mining conveyor. The parameters in the sum of this paper are as follows: (1) A

training set, the specific types an Fig. 1. The mining conveyor.

The main contributions of this paper are as follows: (1) A training set can improve the shown in TABLE I below. I

unique dataset of connection buckles of the U38 model of generalize the defec Fig. 1. The mining conveyor. images, the specific types

shown in TABLE I below.

unique dataset of connection buckles of the U38 model of generalize the defects of the

unique dataset of connection buckles of the U38 mode The main contributions of this paper are as follows: (1) A

unique dataset of connection buckles of the U38 model of

uniming set can improve the

mining powerful transportation belts was created through

on-site data coll The main contributions of this paper are as follows: (1) A

unique dataset of connection buckles of the U38 model of

unimg set can improve the

unimg powerful transportation belts was created through

the risk of overfitt unique dataset of connection buckles of the U38 model of generalize the defects of the mining powerful transportation belts was created through the risk of overfitting, the ion-site data collection and expansion. (2) To ta mining powerful transportation belts was created through the risk of overfitting, the on-site data collection and expansion. (2) To tackle the coughly divided into the challenges of complex backgrounds [15] and varying def on-site data collection and expansion. (2) To tackle the roughly divided into the challenges of complex backgrounds [15] and varying defect set in the ratio of 8:1:1. scales during defect detection, the enhanced model in t challenges of complex backgrounds [15] and varying defect set in the ratio of 8:1:1.

scales during defect detection, the enhanced model in this

paper addressed localization and classification issues in

detect detection. scales during defect detection, the enhanced paper addressed localization and classificaties defect detection. To address the issue of featur loss caused by multiple downsampling of the featured model emphasized focusing o ection. To address the issue of feature information

d by multiple downsampling of the feature map, the

model emphasized focusing on identified targets.

ore, to address inaccuracies in the original model's

on of the los enhanced model emphasized focusing on identified targe

Furthermore, to address inaccuracies in the original mode

computation of the loss function, the enhanced mod

optimization enhanced the detection of small target def Thermore, to address inaccuracies in the original model's

mputation of the loss function for bounding box regression. This

timization enhanced the detection of small target defects

the cometing buckles. (3) The proposed computation of the loss function, the enhanced model
optimized the loss function for bounding box regression. This
optimization enhanced the detection of small target defects
method is straightforward, (3) The proposed det

optimized the loss function for bounding box regression. This
optimization enhanced the detection of small target defects
on the connecting buckles. (3) The proposed detection
equipment, and can uniformly recognize and det optimization enhanced the detection of small target defects
on the connecting buckles. (3) The proposed detection
method is straightforward, does not require additional
types of defects.
II. DATA COLLECTION AND PROCESSING
 on the connecting buckles. (3) The proposed detection

method is straightforward, does not require additional

equipment, and can uniformly recognize and detect multiple

types of defects.

II. DATA COLLECTION AND PROCESSI method is straightforward, does not require additional
equipment, and can uniformly recognize and detect multiple
types of defects.
II. DATA COLLECTION AND PROCESSING
A. Preparation of data
Computing power, algorithms, and equipment, and can uniformly recognize and detect multiple

types of defects.

II. DATA COLLECTION AND PROCESSING

A. Preparation of data

Computing power, algorithms, and data are the three

fundamental elements of artifi types of defects.

II. DATA COLLECTION AND PROCESSING

A. Preparation of data

Computing power, algorithms, and data are the three

fundamental elements of artificial intelligence [16][17],

while the quantity and quality II. DATA COLLECTION AND PROCESSING

A. Preparation of data

Computing power, algorithms, and data are the three

fundamental elements of artificial intelligence [16][17],

while the quantity and quality of data are crucial II. DATA COLLECTION AND PROCESSING

A. Preparation of data

Computing power, algorithms, and data are the three

fundamental elements of artificial intelligence [16][17],

while the quantity and quality of data are crucial *A. Preparation of data*

Computing power, algorithms, and data are the three

fundamental elements of artificial intelligence [16][17],

while the quantity and quality of data are crucial factors

affecting the detection

1 of Computer Science
The dataset in this paper was divided into only two
tegories: normal and damaged. This categorization is based
the understanding that any damage can affect the entire
stem. Therefore, detect the dam **nal of Computer Science**
The dataset in this paper was divided into only two
categories: normal and damaged. This categorization is based
on the understanding that any damage can affect the entire
system. Therefore, detec **nal of Computer Science**
The dataset in this paper was divided into only two
categories: normal and damaged. This categorization is based
on the understanding that any damage can affect the entire
system. Therefore, detec **nal of Computer Science**
The dataset in this paper was divided into only two
categories: normal and damaged. This categorization is based
on the understanding that any damage can affect the entire
system. Therefore, detec **nal of Computer Science**

The dataset in this paper was divided into only two

categories: normal and damaged. This categorization is based

on the understanding that any damage can affect the entire

system. Therefore, **replace to the matrix of Computer Science**
The dataset in this paper was divided into only two
categories: normal and damaged. This categorization is based
on the understanding that any damage can affect the entire
syste **If** of **Computer Science**

The dataset in this paper was divided into only two

tegories: normal and damaged. This categorization is based

the understanding that any damage can affect the entire

stem. Therefore, detect **nal of Computer Science**

The dataset in this paper was divided into only two

categories: normal and damaged. This categorization is based

on the understanding that any damage can affect the entire

system. Therefore,

replacement should be halted.

Due to the specificity of the rest

damage images + 400 normal

original images (resolution: 300

from on-site shooting, but the ac

from on-site shooting, but the ac

requires a large amount Due to the specificity of the redamage images + 400 normal
original images (resolution: 30
from on-site shooting, but the accuracies of control
incomes a large amount of data states of the specific speeding but the accurac damage images + 400 no
original images + 400 no
original images (resolutio
from on-site shooting, but
requires a large amount of the example of effects, so here the original
effects, so here the original expanded [18]. Aft original images (resolution: 3

from on-site shooting, but the a

requires a large amount of data s

requires a large amount of data s

requires a large amount of data s

expanded [18]. After the expans

rig. 1. The mining **nal of Computer Science**
The dataset in this paper was divided into only two
categories: normal and damaged. This categorization is based
on the understanding that any damage can affect the entire
system. Therefore, dete **From the shooting in the accuracy of damage detection** is based on the understanding that any damage can affect the entire system. Therefore, detect the damage and sound an alarm, allowing the field technician to decide The dataset in this paper was divided into only two
categories: normal and damaged. This categorization is based
on the understanding that any damage can affect the entire
system. Therefore, detect the damage and sound an The dataset in this paper was divided into only two categories: normal and damaged. This categorization is based on the understanding that any damage can affect the entire system. Therefore, detect the damage and sound an The dataset in this paper was divided into only two categories: normal and damaged. This categorization is based on the understanding that any damage can affect the entire system. Therefore, detect the damage and sound an categories: normal and damaged. This categorization is based
on the understanding that any damage can affect the entire
system. Therefore, detect the damage and sound an alarm,
allowing the field technician to decide whet on the understanding that any damage can affect the entire
system. Therefore, detect the damage and sound an alarm,
allowing the field technician to decide whether the
replacement should be halted.
Due to the specificity system. Therefore, detect the damage and sound an alarm,
allowing the field technician to decide whether the
replacement should be halted.
Due to the specificity of the research object, only 961 (561
damage images + 400 n allowing the field technician to decide whether the replacement should be halted.

Due to the specificity of the research object, only 961 (561 damage images + 400 normal connection buckle images) original images (resolut replacement should be halted.

Due to the specificity of the research object, only 961 (561

damage images + 400 normal connection buckle images)

original images (resolution: 3060 × 4080) were obtained

from on-site shoo Due to the specificity of the research object, only 961 (561 damage images + 400 normal connection buckle images) original images (resolution: 3060×4080) were obtained from on-site shooting, but the accuracy of damage damage images + 400 normal connection buckle images)
original images (resolution: 3060×4080) were obtained
from on-site shooting, but the accuracy of damage detection
requires a large amount of data support for connec original images (resolution: 3060×4080) were obtained
from on-site shooting, but the accuracy of damage detection
requires a large amount of data support for connecting buckle
defects, so here the original images were from on-site shooting, but the accuracy of damage dete
requires a large amount of data support for connecting bu
defects, so here the original images were data enhance
expanded [18]. After the expansion to 3366 data sets,

Typology Revolve Noises Glare Darkness Zoom Contrast Total

Training 356 511 383 524 441 488 2703

validation 40 75 50 53 56 52 326

Test sets 48 78 36 53 57 65 337

Total 444 664 469 630 554 605 3366

B. Sample labeling
 manument

Training 356 511 383 524 441 488 2703

validation 40 75 50 53 56 52 326

Test sets 48 78 36 53 57 65 337

Total 444 664 469 630 554 605 3366

B. Sample labeling

In this paper, Make Sense software was used to ann The label was Defects WC (Defects Will Occur); the damage category was 0, and the label was DefectsOC (Defects Occurred).

Alle abel was DefectsWC (Defects Will Occur); the damage category was 0, and the label was DefectsO Validation 40 75 50 53 56 52 326

rest sets 48 78 36 53 57 65 337

Total 444 664 469 630 554 605 3366
 B. Sample labeling

In this paper, Make Sense software was used to annotate

the images, as illustrated in Fig. 4. Th Occurred).

Example 18 Solution Scale-awareness, task-awareness

The principle is as follows:

The output of L different lever

backbone is:

Fig. 4. Image annotation process.

III. YOLOV7 MODEL IMPROVEMENTS

A. YOLOV7 General Stru **Entity of the principle is as follows:**

The principle is as follows:

The output of L different level

backbone is:

Fig. 4. Image annotation process.

III. YOLOV7 MODEL IMPROVEMENTS

The feature pyramid is rescal

III. The output of L different lackbone is:

Fig. 4. Image annotation process.

The feature pyramid is res

III. YOLOV7 MODEL IMPROVEMENTS and feature map:
 $F = \frac{1}{\sqrt{2}}$

A. YOLOV7 General Structure

Consists of four primary Fig. 4. Image annotation process.

The feature pyramid is

III. YOLOV7 MODEL IMPROVEMENTS

The feature pyramid is

The Facture pyramid is

The Facture pyramid is

The Facture pyramid is

The Facture pyramid is

The Factur Fig. 4. Image annotation process.

III. YOLOV7 MODEL IMPROVEMENTS and feature pyramid is resconting the feature of the SOLOV7 General Structure

The FOLOV7 General Structure (Secretive described in this article beight of modules that maintain the initial gradient path, thereby The teature pyramid is
 $\frac{1}{2}$ III. YOLOv7 MODEL IMPROVEMENTS and feature map:
 $\frac{1}{2}$ The YOLOv7 Ceneral Structure

The YOLOv7 (26) architecture described in this article

the median level feature, and the median l III. YOLOV7 MODEL IMPROVEMENTS

A. YOLOV7 General Structure

The YOLOV7 [26] architecture described in this article

consists of four primary components: Input, Backbone, Neck,

and Ievel feature, and C is

and Head. The A. *YOLOv7 General Structure* Where L is the number of The YOLOv7 [26] architecture described in this article height of the median level consists of four primary components: Input, Backbone, Neck, median level feature, an A. YOLOv7 General Structure

The YOLOv7 [26] architecture described in this article

consists of four primary components: Input, Backbone, Neck, median level feature, and

enhance the data volume and increase the batch si The YOLOv7 [26] architecture described in this article

consists of four primary components: Input, Backbone, Neck,

and Head. The network structure is illustrated in Fig 5. To

enhance the data volume and increase the ba consists of four primary components: Input, Backbone, Neck, median level feature, and
and Head. The network structure is illustrated in Fig 5. To
feature.
chance the data volume and increase the batch size, the
fusion cha and Head. The network structure is illustrated in Fig 5. To

enhance the data volume and increase the batch size, the

Mosaic data augmentation technique is applied to the Input.

The Backbone network consists of several enhance the data volume and increase the batch size, the

Mosaic data augmentation technique is applied to the Input.

The Backbone network consists of several layers, including

composed to the CBS control and MPConv. EL Mosaic data augmentation technique is applied to the Input.

The Backbone network consists of several layers, including

CBS, ELAN, and MPConv. ELAN consists of multiple CBS

modules that maintain the initial gradient pat The Backbone network consists of several layers, including $F \in R^{L\times S \times C}$

CBS, ELAN, and MPConv. ELAN consists of multiple CBS

modules that maintain the initial gradient path, thereby from the traditional method of di-CBS, ELAN, and MPConv. ELAN consists of multiple CBS

modules that maintain the initial gradient path, thereby

enhancing the network's learning potential and enabling

the fraction on all dimensio

better acquisition of capability.

al of Computer Science
 B. YOLOv7 Algorithm Improvement
 dd Dynamic Head

Conveyor belt buckle defect detection does not require

ponsideration of the classification problem; therefore, it is **Assume of Computer Science**
 B. YOLOv7 Algorithm Improvement
 Add Dynamic Head

Conveyor belt buckle defect detection does not

consideration of the classification problem; therefore

essential to combine localization **Computer Science**
 EXECUCA Algorithm Improvement
 Conveyor belt buckle defect detection does not require
 Conveyor belt buckle defect detection does not require
 Conveyor belt buckle defect detection does not requi nal of Computer Science
 B. YOLOv7 Algorithm Improvement
 Add Dynamic Head

Conveyor belt buckle defect detection does not require

consideration of the classification problem; therefore, it is

essential to combine nal of Computer Science
 B. YOLOv7 Algorithm Improvement
 Add Dynamic Head

Conveyor belt buckle defect detection does not require

consideration of the classification problem; therefore, it is

essential to combine lo **nal of Computer Science**
 B. YOLOv7 Algorithm Improvement
 Add Dynamic Head

Conveyor belt buckle defect detection does not require

consideration of the classification problem; therefore, it is

essential to combine **nal of Computer Science**
 B. YOLOv7 Algorithm Improvement
 Add Dynamic Head

Conveyor belt buckle defect detection does not require

consideration of the classification problem; therefore, it is

essential to combine **1 of Computer Science**

3. *YOLOv7 Algorithm Improvement*
 d Dynamic Head

Conveyor belt buckle defect detection does not requirinsideration of the classification problem; therefore, it is

sential to combine localizat **11 of Computer Science**

3. *YOLOv7 Algorithm Improvement*
 Id Dynamic Head

Conveyor belt buckle defect detection does not require

msideration of the classification problem; therefore, it is

sential to combine local B. YOLOv7 Algorithm Improvement
Add Dynamic Head
Conveyor belt buckle defect detection does
consideration of the classification problem; the
essential to combine localization and c
effectively. DyHead (Dynamic Head) [19]
 CONTA CONTEXECT CONTEX CONTEX CONTEX CONTEX CONTENTIFY (1)
 CONTEX CONTEX CONTE *in i i F F* 3. *YOLOv7 Algorithm Improvement*
 Id Dynamic Head

Conveyor belt buckle defect detection does not require

nsideration of the classification problem; therefore, it is

sential to combine localization and classification Add Dynamic Head

Conveyor belt buckle defect detection does a

consideration of the classification problem; then

essential to combine localization and cleffectively. DyHead (Dynamic Head) [19]

scale-awareness, task-awa *Leare Leare Contention Concerering Metallassification problem; therefore, it is

<i>Leare learestication and classification*
 Coyamic Head) [19] combines
 P F i F i F i f i f i c Coyamic set and moderation of the classification problem; therefore, it is
sential to combine localization and classification
fectively. DyHead (Dynamic Head) [19] combines
ale-awareness, task-awareness, and spatial-awareness.
The princi **Example 12**
 L Society Undelected Section does not require

Louckle defect detection does not require

the classification problem; therefore, it is

sholing localization and classification

sholing and (Dynamic Head) [

$$
F_{in} = \left\{ F_i \right\}_{i=1}^L \tag{1}
$$

$$
F \in R^{L \times H \times W \times C} \tag{2}
$$

essential to combine localization and classification
effectively. DyHead (Dynamic Head) [19] combines
scale-awareness, task-awareness, and spatial-awareness.
The principle is as follows:
The output of L different levels o effectively. DyHead (Dynamic Head) [19] combines
scale-awareness, task-awareness, and spatial-awareness.
The principle is as follows:
The output of L different levels of feature maps from the
backbone is:
 $F_{in} = \{F_i\}_{i=1}$ feature. The principle is as follows:

The output of L different levels of feature maps from the

ckbone is:
 $F_{in} = \{F_i\}_{i=1}^{L}$ (1)

The feature pyramid is rescaled to obtain a four-dimensio

1 feature map:
 $F \in R^{L \times H \times W \times C}$ The output of L different levels of feature maps from the

backbone is:
 $F_{in} = \{F_i\}_{i=1}^L$ (1

The feature pyramid is rescaled to obtain a four-dimensi

and feature map:
 $F \in R^{L \times H \times W \times C}$ (2

Where L is the number of

$$
F \in R^{L \times S \times C} \left(S = H \times W \right) \tag{3}
$$

 $F_{in} = \{F_i\}_{i=1}^N$ (1)
The feature pyramid is rescaled to obtain a four-dimensio
I feature map:
 $F \in R^{L \times H \times W \times C}$ (2)
Where L is the number of levels in the pyramid, H is the
gight of the median level feature, W is the The feature pyramid is rescaled to obtain a four-dimensio

nal feature map:
 $F \in R^{L \times H \times W \times C}$ (2)

Where L is the number of levels in the pyramid, H is the

height of the median level feature, W is the width of the

med splitting the serial attention of the median level feature in $F \in R^{L \times H \times W \times C}$ (2)
Where L is the number of levels in the pyramid, H is the
height of the median level feature, W is the width of the
median level feature, $F \in R^{L \times H \times W \times C}$
Where L is the number of levels in the pyramid, H i
height of the median level feature, W is the width of
median level feature, and C is the channel of the median
feature.
The four-dimensional feature m median level readare, and C is the channel of diature.

The four-dimensional feature map is furthe

a three-dimensional tensor:
 $F \in R^{L \times S \times C}$ ($S = H \times W$)

The traditional method of directly learnin

function on all dime

$$
W(F) = \Pi_C \left(\Pi_S \left(\Pi_L(F) \cdot F \right) \cdot F \right) \cdot F \tag{4}
$$

Mgorithm Improvement
 Algorithm Improvement
 Head
 Etch buckle defect detection does not require

for the classification problem; therefore, it is

combine localization and classification

(Dynamic Head) [19] co **1 of Computer Science**

2. *YOLOv7 Algorithm Improvement*
 d Dynamic Head
 d Dynamic Head

colvey bet buckle defect detection does not require

ensideration of the classification problem; therefore, it is

ensided (D The four-dimensional feature map is further reshaped into
three-dimensional tensor:
 $F \in R^{L \times S \times C}$ ($S = H \times W$) (3)
The traditional method of directly learning the attention
notion on all dimensions is computationally larg in the non-dimensional reading is further restapled into
a three-dimensional tensor:
 $F \in R^{L \times S \times C}$ ($S = H \times W$) (3)
The traditional method of directly learning the attention
function on all dimensions is computationally l $F \in R^{L \times S \times C}$ ($S = H \times W$) (3)
The traditional method of directly learning the attention
function on all dimensions is computationally large. So it is
split into three serial attentions and each of them focuses on a
singl F $\in R^{m,n}$ ($S = H \times W$) (3)

The traditional method of directly learning the attention

function on all dimensions is computationally large. So it is

split into three serial attentions and each of them focuses on a

singl The traditional method of directly learning the attention
function on all dimensions is computationally large. So it is
split into three serial attentions and each of them focuses on a
single dimension only.
 $W(F) = \Pi_c (\Pi_s (\Pi$

(a) DyHead Block

mechanism into neural networks is an important way to
 $Add Squareze-and-Excitation Networks$

The networks of the secondary target detector process

Tig. 6. DyHead detailed configuration.

Add Squeeze-and-Excitation Networks

to capture the most sa enhance the feature representation of convolutional neural

information contents in the feature representation of convolutional neural

information and squeeze-and-Excitation Networks

The feature representation of convol The Stephenture is schemetically shown in Eig. 7.

The Stephend Molecules applied to the secondary target detector process

Fig. 6. DyHead detailed configuration.

Add Squeeze-and-Excitation Networks

For defect detection Example a blocks applied to the secondary target detector process

Fig. 6. DyHead detailed configuration.

Add Squeeze-and-Excitation Networks

For defect detection of conveyor belt buckles, it is essential

to capture th (c) DyHead blocks applied to the secondary target detector process

Fig. 6. DyHead detailed configuration.

Add Squeeze-and-Excitation Networks

For defect detection of conveyor belt buckles, it is essential

to capture t information The SE block structure is schematically shown in Fig. 7:
 $\begin{bmatrix}\nF_{\alpha}(*,y) \\
\vdots \\
F_{\alpha}(*,y)\n\end{bmatrix}$

Na Squeeze-and-Excitation Networks

For defect detection of conveyor belt buckles, it is essential

capture the most salient

ERECALL CONDETERMINE CONTROLLER CONSERVATION
 ERECALL CONSERVATIONS

(b) SENet added to SPPCSPC module

Fig. 8. SENet was added to the YOLOV7-specific location.

Add the loss function MPDIoU

Current target detectors **SPPCSPC**
 however, CBS
 however, CBS

(b) SENet added to SPPCSPC module

Fig. 8. SENet was added to the YOLO τ -specific location.

Add the loss function MPDIoU

Current target detectors of the YOLO family [21-26] SENET MANDON 3

(BS + Manpool 3)

(b) SENet added to SPPCSPC module

Fig. 8. SENet was added to the YOLO 7-specific location.

Add the loss function MPDIoU

Current target detectors of the YOLO family [21-26] all

rely on **Fig. 3.** SENet added to SPPCSPC module
Fig. 8. SENet was added to the YOLOV7-specific location.
Add the loss function MPDIoU
Current target detectors of the YOLO family [21-26] all
rely on the Bounding Box Regression (BB (b) SENet added to SPPCSPC module
Fig. 8. SENet was added to the YOLOV7-specific location.
Add the loss function MPDIoU
Current target detectors of the YOLO family [21-26] all
rely on the Bounding Box Regression (BBR) mod (b) SENet added to SPPCSPC module
Fig. 8. SENet was added to the YOLOv7-specific location.
Add the loss function MPDIoU
Current target detectors of the YOLO family [21-26] all
rely on the Bounding Box Regression (BBR) mod (b) SENet added to SPPCSPC module
Fig. 8. SENet was added to the YOLOv7-specific location.
Add the loss function MPDIoU
Current target detectors of the YOLO family [21-26] all
rely on the Bounding Box Regression (BBR) modu *As in Eig. 9, MPDIoU* serves as the boundary loss.

As in Fig. 9, MPDIoU serves and the YOLO family [21-26] all y on the Bounding Box Regression (BBR) module to termine object positions. Most of the current loss function

L_{MPDIOU} [27].

below: The Mexican Series as the boundary loss.

TABLE II. EXPERIMENTATION AND ANALYSIS

Experimental environment and evaluation indicators

ne experimental environment is configured in TABLE II

W:

TABLE II. EXPERIMENTAL ENVIRO

IAENG International Journal of Computer Science
The optimizer Adam is used to update the network metrics Precision and Recaller
are the stratively. In this paper, after conducting several F1-score is used to judge,
rameter **IAENG International Journal of Computer Scien**
The optimizer Adam is used to update the network metrics Precision and Reparameters iteratively. In this paper, after conducting several F1-score is used to judge, parameter-**IAENG International Journal of Computer Science**
The optimizer Adam is used to update the network metrics Precision and Recall
parameter-seeking optimization experiments, as illustrated in Precision and Recall. The resul IAENG International Journal of Computer Science
The optimizer Adam is used to update the network metrics Precision and Reca
parameters iteratively. In this paper, after conducting several F1-score is used to judge, v
param **IAENG International Journal of Computer Scie**
The optimizer Adam is used to update the network metrics Precision and R
parameters iteratively. In this paper, after conducting several F1-score is used to judge
parameter-se **IAENG International Journal of Computer Science**

The optimizer Adam is used to update the network metrics Precision and Recall

parameter-seeking optimization experiments, as illustrated in F1-score is used to judge, wh **EXERG Internal**

The optimizer Adam is used to update the

parameters iteratively. In this paper, after conduct

parameter-seeking optimization experiments, as ill

Fig. 10, the initial learning rate is set to 0.01, and

Example 1.1 the subset of the stacked 6 time of the experimental evaluation experiments.

The experiment, the parameters Precision, ^{0. 05}
 B. 16 **B.** 32 **D.** (b) DyF
 B. 16 **B.** 32 **D.** (b) DyF

Epoch
 B. 10. Parameter-secking optimization experiments.
 B. In this experiment, the parameters Precision, Recall, 6 time
 EXPREMAGEALS (mean Aver *DyHead Module Comparison Experiment with Different*
 DyHead is stacked 6 times

Fig. 10. Parameter-seeking optimization experiments.

In this experiment, the parameters Precision, Recall,
 DyHead Module FLOPs, which r $0.00 + \frac{1}{0.200} + \frac{1}{200}$ $\frac{1}{400} + \frac{1}{600}$ $\frac{1}{600} + \frac{1}{1000}$ $\frac{1}{1200}$
 Nodel loss function curve under different batch_sizes

Fig. 10. Parameter-seeking optimization experiments.

In this experiment, th Model loss function curve under different batch sizes

Expediment and the magnification experiments.

The number of Medal of the state is the F1-score is 0.76,

In this experiment, the parameters Precision, Recall, 6 time (b) Model loss function curve under different batch_sizes

Fig. 10. Parameter-seeking optimization experiments.

In this experiment, the parameters Precision, Recall, 6 times, the F1-score is

mAP@0.5 (mean Average Precis Fig. 10. Parameter-seeking optimization experiments.

From Fig. 11, it can be strimes, the F1-score is 0.76,

mAP@0.5 (mean Average Precision, IOU=0.5), and the

computational FLOPs, which reflect the complexity of the

m

nal of Computer Science

metrics Precision and Recall conflict. In this case, the

F1-score is used to judge, which is the harmonic mean of

Precision and Recall. The results of the judgment are shown

in Fig. 11. **nal of Computer Science**

metrics Precision and Recall conflict. In this case, the

F1-score is used to judge, which is the harmonic mean of

Precision and Recall. The results of the judgment are shown

in Fig. 11. **nal of Computer Science**

metrics Precision and Recall conflict. In this case, the

F1-score is used to judge, which is the harmonic mean of

Precision and Recall. The results of the judgment are shown

in Fig. 11. **nal of Computer Science**

metrics Precision and Recall conflict. In

F1-score is used to judge, which is the harm

Precision and Recall. The results of the judgr

in Fig. 11.

DyHead is stacked 6 times

In the paper, $\frac{0.4}{0.0}$ and $\frac{0.6}{0.0}$ and $\frac{0.8}{0.0}$ and $\frac{0.8}{0.0}$

In the paper, the paper, to comparison.

In the paper, the paper, to verify the effectiveness of the SENet [20] **and the CHAM**
 attention mechanism for definition $\frac{a_4}{a_4} = \frac{a_5}{a_5}$ and $\frac{a_6}{a_6} = \frac{a_7}{a_7}$

Fig. 11. F1-score comparison.

From Fig. 11, it can be seen that when DyHead is stacked 4

times, the F1-score (b) DyHead is stacked 6 times
Fig. 11. F1-score comparison.
From Fig. 11, it can be seen that when DyHead is stacked 4
times, the F1-score is 0.76, whereas when DyHead is stacked
6 times, the F1-score is only 0.74. Therefo (b) DyHead is stacked 6 times
Fig. 11. F1-score comparison.
From Fig. 11, it can be seen that when DyHead is stacked 4
times, the F1-score is 0.76, whereas when DyHead is stacked
6 times, the F1-score is only 0.74. Therefo Fig. 11. F1-score comparison.

From Fig. 11, it can be seen that when DyHead is stacked 4

times, the F1-score is 0.76, whereas when DyHead is stacked

6 times, the F1-score is only 0.74. Therefore, the model

performs bes Frg. 11. F1-score comparison.

From Fig. 11, it can be seen that when DyHead is stacked 4

times, the F1-score is 0.76, whereas when DyHead is stacked

6 times, the F1-score is only 0.74. Therefore, the model

performs bes From Fig. 11, it can be seen that when DyHead is stacked 4
times, the F1-score is 0.76, whereas when DyHead is stacked
6 times, the F1-score is only 0.74. Therefore, the model
performs best when DyHead is stacked 4 times. Comparative Experiments on Attentional Mechanisms

In the paper, to verify the effectiveness of the SENet [20]

ittention mechanism for detecting defects in the homemade

connection buckling dataset, we integrated the CBA

moder, were used as the experimental evaluation metrics. B. Modeling and experimental results DyHead Module Comparison Experiment with Different Number of Modules The number of control blocks is generally used to evaluate the efficiency of the Dynamic Head [19]. DyHead stacking counts comparison experiments are shown below in TABLE Ш.					In the paper, to verify the effectiveness of the SENet [20] attention mechanism for detecting defects in the homemade connection buckling dataset, we integrated the CBAM (Channel Attention) [28], CA (Coord Attention) [29], and SA (Shuffle Attention) [30] attention mechanisms, which have demonstrated superior performance at this stage. The results of the comparative experiments are presented in TABLE IV. TABLE IV. COMPARATIVE EXPERIMENTS ON ATTENTIONAL MECHANISMS.					
		MODULES	TABLE III. COMPARATIVE EXPERIMENTAL RESULTS OF DIFFERENT DYHEAD		Model YOLOv7	Precision(%) 73.1	$Recall(\%)$ 77.8	mAP@0.5(%) 74.6	FLOPs(G) 100.9	
Number	Precision(%)	Recall(%)	mAP@0.5(%)	FLOPs(G)	YOLOv7+SENet	74.7	78.0	74.9	102.5	
θ	73.1	77.8	74.6	100.9	YOLOv7+CBAM YOLOv7+CA	74.3 72.3	76.6 73.9	73.3 72.5	105.1 101.1	
	70.2 73.2	69.8 78.2	66.3 74.7	103.4 105.9	YOLOv7+SA	73.6	75.0	74.8	105.1	
6	72.4	71.9	71.7	108.4						
			From the data in TABLE III, it can be seen that when the DyHead module is stacked 4 times and 6 times, the two		Analysis of Experimental Results of Improved Model for Detection of Multiple Types of Defects			The loss function MPDIoU was added at the end of the		
					Volume 51. Issue 10. October 2024. Pages 1663-1671					

IAENG International Journal of Computer Science

enhanced model to optimize the boundary regression loss

function. To distinguish it, the enhanced YOLOv7 model was

referred to as YOLOv7 m in this paper. a comparison of t **IAENG International Journal of Computer Science**

enhanced model to optimize the boundary regression loss

function. To distinguish it, the enhanced YOLOv7 model was

referred to as YOLOv7 m in this paper. a comparison o **IAENG International Journal of Computer Science**

enhanced model to optimize the boundary regression loss

function. To distinguish it, the enhanced YOLOv7 model was

referred to as YOLOv7_m in this paper. a comparison o **EXECUTE:** IAENG International Journal of Computer Science

enhanced model to optimize the boundary regression loss

function. To distinguish it, the enhanced YOLOv7 model was

referred to as YOLOv7_m in this paper. a com **IAENG I**

enhanced model to optimize the bounds

function. To distinguish it, the enhanced Y

referred to as YOLOv7_m in this paper. a

model before and after the enhancement

12 below.
 $\begin{bmatrix}\n\frac{1.0}{1.01} & \frac{1.000007}{$

0.2

0.75

0.01

0.01

0.01

0.01

0.01

0.01

0.001

0.001

0.001

0.001

0.001

0.001

0.0001

0.00 original YOLOv7 model or the enhanced YOLOv7_m model. 1993

Fig. 12. Comparison chart of experimental results.

Fig. 12. Comparison chart of experimental results.

From the above image, it can be observed that as the number of iterations increases, both Precision and Recall of map and the enhanced YOLOv7_m

The endanglemental results.

Fig. 12. Comparison chart of experimental results.

From the above image, it can be observed that as the

number of iterations increases, both Precision and R are higher than those of the original YOLOv7 model
and the original YOLOv7 model with the original $\frac{1}{200}$ and $\frac{1}{200}$ are higher than the original Nove image, it can be observed that as the number of iterations i Epoch

Fig. 12. Comparison chart of experimental results.

Fig. 12. Comparison chart of experimental results.

From the above image, it can be observed that as the

number of iterations increases, both Precision and Recal (c) Recall curve
Fig. 12. Comparison chart of experimental results.

From the above image, it can be observed that as the

number of iterations increases, both Precision and Recall also

increase. The fluctuations gradual Example 1. 12. Comparison chart of experimental results.
From the above image, it can be observed that as the
mber of iterations increases, both Precision and Recall also
rease. The fluctuations gradually decrease and eve From the above image, it can be observed that as the number of iterations increases, both Precision and Recall also increase. The fluctuations gradually decrease and eventually stabilize. No overfitting phenomenon is obse From the above image, it can be observed that as the number of iterations increases, both Precision and Recall also increase. The fluctuations gradually decrease and eventually stabilize. No overfitting phenomenon is obse number of iterations increases, both Precision and Recall also
increase. The fluctuations gradually decrease and eventually
stabilize. No overfitting phenomenon is observed in either the
original YOLOv7 model or the enhan increase. The fluctuations gradually decrease and eventually stabilize. No overfitting phenomenon is observed in either the original YOLOv7 model or the enhanced YOLOv7_m model.
From the three figures in Fig. 12, it can b

TABLE V. COMPARISON OF ABLATION EXPERIMENTS BY DETECTION ALGORITHM.

THERE-CONNECT AREA CONDUCED AND CONTROLL SENET DYHead4 MPDIoU P(%) R(%) mAP@0.5(%)

THERE V. COMPARISON OF ABLATION EXPERIMENTS BY DETECTION ALGORITHM.

0.75 0.70 350 100 200 300 Epoch TABLE V. COMPARISON OF ABLATION EXPERIMENTS BY DETECTION ALGORITHM.	400 400					convergence accelerates, and the performance improv To further validate the superiority of the er algorithm, this paper also selected some of the main defect detection algorithms at this stage and cor comparative ablation experiments. The results experiments are presented in TABLE V.	
Arithmetic	SENet	DyHead4	MPDIoU	$P(\%)$	$R(\%)$	$mAP@0.5(\%)$	
Faster R-CNN[31]				65.2	60.0	63.3	
Faster R-CNN+SENet	$\sqrt{}$			65.8	61.9	64.2	
Faster R-CNN+DyHead				69.3	66,4	64.5	
Faster R-CNN_m	V		V	72.0	69.6	71.3	
SSD [7]				66.1	62.4	66.0	
SSD+SENet	√			66.9	62.3	66.2	
SSD+DyHead		V		67.4	64.3	67.5	
SSD m	$\sqrt{}$	V	√	68.7	66.8	67.7	
YOLOv4 [23]				69.1	70.2	71.5	
YOLOv4+SENet	$\sqrt{}$			69.2	71.4	68.8	
YOLOv4+DyHead		V		71.2	69.7	72.3	
YOLOv4 m	√		√	70.1	70.4	69.2	
YOLOv7 [26]				73.1	77.8	74.6	
YOLOv7+SENet	$\sqrt{}$			74.7	78.0	74.9	
YOLOv7+DyHead				73.2	78.2	74.7	
YOLOv7_m	$\sqrt{}$		$\sqrt{}$	79.3	83.2	78.8	
YOLOv8				69.8	71.4	70.9	
YOLOv8+SENet	$\sqrt{}$			73.5	71.6	73.2	
YOLOv8+DyHead				72.9	74.1	73.9	
YOLOv8 m				73.4	78.8	74.7	

 $\frac{2}{3}$ The NOLOV⁻¹ Superinted that the NOLOV⁻¹ Superinted that the Newton and the system. This accuracy is necessary is necessary is necessary is necessary is necessary is the system. This accuracy is necessary is $\begin{array}{c|c|c|c|c} \hline \end{array}$

algorithm significantly improves all aspects of defect

algorithm significantly improves all aspects of defect

Alternation compared with the original YOLOv7 model, the accuracy of
 $\begin{array}{c|c|c|$ $\frac{1}{200}$

Fronton² absent all the secure of the according to the algorithm significantly improves all according to the according of the enhance, by the aformation of the secure of the set of the set of the set of the Fig. 13. Comparison Recall mAP@0.5

Precision Recall mAP@0.5

Precision Recall mAP@0.5

Fig. 13. Comparison chart of ablation experiments.

The YOLOv8 model, as illustrated in TABLE V and Fig. 13, the SENet

The YOLOv8 mod Fig. 13. Comparison Recall mAP@0.5

Fig. 13. Comparison chart of ablation experiments.

Fig. 13. Comparison chart of ablation experiments.

As demonstrated in TABLE V and Fig. 13, the SENet in comprehensive defect-type

a movel dataset comprising criterium

Fig. 13. Comparison chart of ablation experiments.

Fig. 13. Comparison chart of ablation experiments.

As demonstrated in TABLE V and Fig. 13, the SENet The YOLOv8 model, which has att Precision Recall mAP@0.5

Fig. 13. Comparison chart of ablation experiments.

The YOLOv8 model, as illustrated in TABLE

As demonstrated in TABLE V and Fig. 13, the SENet The YOLOv8 model, which

attention mechanism and D Fig. 13. Comparison chart of ablation experiments.

The YOLOv8 model, as illustrated in TABLE N

As demonstrated in TABLE V and Fig. 13, the SENet

attention mechanism and DyHead can somewhat enhance the

original model's Fig. 13. Comparison chart of ablation experiments.

The YOLOv8 model, which the momental manufoly

attention mechanism and DyHead can somewhat enhance the conduct comparison experimental meadly detection performance. Howev As demonstrated in TABLE V and Fig. 13, the SENet
attention mechanism and DyHead can somewhat enhance the
original model's detection performance. However, the final
experimental results demonstrate that the YOLOv7_m
algor attention mechanism and DyHead can somewhat enhance the

original model's detection performance. However, the final

experimental results demonstrate that the YOLOv7_m

algorithm significantly improves all aspects of defec iginal model's detection performance. However, the final

improved model YOLOv7_m.

perimental results demonstrate that the YOLOv7_m

perimental in Superinte that the YOLOv7_m

presented in Table VII.

tection compared to experimental results demonstrate that the YOLOv7_m
algorithm significantly improves all aspects of defect
detection compared to other mainstream algorithms.
Compared in Table VII. NuMBER OF EXPANDED
the enhanced YOLOv7_m algorithm significantly improves all aspects of defect
detection compared to other mainstream algorithms.
Compared with the original YOLOv7 model in detecting defects in
compared YOLOv7_m model in detecting defects in com detection compared to other mainstream algorithms.

TABLE VI. NU

Compared with the original YOLOv7 model, the accuracy of

the enhanced YOLOv7_m model in detecting defects in

connecting buckles has increased by 6.2%, al the enhanced YOLOv7_m model in detecting defects in

connecting buckles has increased by 6.2%, allowing for

Improved localization of faulty components. The Recall rate

has improved by 5.4%, decreasing the defet leakage r connecting buckles has increased by 6.2%
improved localization of faulty components.
has improved by 5.4%, decreasing the defect
the model. Additionally, the mean Average P
detection accuracy has improved by 4.2%, r
suitab proved localization of faulty components. The Recall rate

in more in more in simple accuration (mAP)

encode. Additionally, the mean Average Precision (mAP)

frest sets

frection accuracy has improved by 4.2%, making it

The improved by 5.4%, decreasing the defect leakage rate in
the model. Additionally, the mean Average Precision (mAP)
suitable for detecting defects in connecting buckles.
To further verify that the improved YOLOv7_m mode the model. Additionally, the mean Average Precision (mAP)

detection accuracy has improved by 4.2%, making it more

suitable for detecting defects in connecting buckles.

To further verify that the improved YOLOv7_m model detection accuracy has improved by 4.2%, making it more

suitable for detecting defects in connecting buckles.

To further verify that the improved YOLOv7_m nodel has

a practical effect on the detection of connection buck

er.pg

er.pg

and the contract of the second type of defects a er results

er ripg

and the types of defects that need to be overhauled when the

equipment is shut down and those that may lead to serious

equipment failures and thus require immediate shutdown for

treatment. This pape treatment. This paper called the second type of defects as
equipment is shut down and those that may lead to serious
equipment failures and thus require immediate shutdown for
treatment. This paper called the second type o critical defects. In addition, three or more consecutive
connection, the present of defects that need to be overhauled when the
equipment is shut down and those that may lead to serious
equipment failures and thus require non-critical defects that need to be overhauled when the equipment is shut down and those that may lead to serious equipment failures and thus require immediate shutdown for treatment. This paper called the second type of The precise identification of significant flaws in the metal-
the precise is tresults
tresults
tresults
the precise identification and those that may lead to serious
uipment failures and thus require immediate shutdown for **CONSECTED ANDEL CONFIDENTIFICATES**

The types of defects that need to be overhauled when the

equipment is shut down and those that may lead to serious

equipment failures and thus require immediate shutdown for

treatmen

Functionists
EXECUTE:
 EXECUTE:
 EXECUTE:
 EXECUTE:
 ENDIFIENT:
 ENDI rest results
the types of defects that need to be overhauled when the
equipment is shut down and those that may lead to serious
equipment failures and thus require immediate shutdown for
treatment. This paper called the se a test results
the types of defects that need to be overhauled when the
equipment is shut down and those that may lead to serious
equipment failures and thus require immediate shutdown for
treatment. This paper called the the types of defects that need to be overhauled when the equipment is shut down and those that may lead to serious equipment failures and thus require immediate shutdown for treatment. This paper called the second type of the types of defects that need to be overhauled when the equipment is shut down and those that may lead to serious equipment failures and thus require immediate shutdown for treatment. This paper called the second type of accidents. uipment failures and thus require immediate shutdown for atment. This paper called the second type of defects as tical defects. In addition, three or more consecutive n-critical defect types were categorized as critical de treatment. This paper called the second type of defects as critical defects. In addition, three or more consecutive non-critical defect types were categorized as critical defects. The precise identification of significant critical defects. In addition, three or more consecutive
non-critical defect types were categorized as critical defects.
The precise identification of significant flaws in the
connection buckle is essential for maintaining non-critical defect types were categorized as critical defects.
The precise identification of significant flaws in the
connection buckle is essential for maintaining the safe
functioning of the mine transportation system. The precise identification of significant flaws in the
nnection buckle is essential for maintaining the safe
netioning of the mine transportation system. To ensure the
fectiveness of the detection model, the model must exh connection buckle is essential for maintaining the safe
functioning of the mine transportation system. To ensure the
effectiveness of the detection model, the model must exhibit
a high level of accuracy in identifying crit functioning of the mine transportation system. To ensure the effectiveness of the detection model, the model must exhibit a high level of accuracy in identifying critical defects within the system. This accuracy is necess effectiveness of the detection model, the model must exhibit
a high level of accuracy in identifying critical defects within
the system. This accuracy is necessary for promptly detecting
potential hazards and preventing th

a high level of accuracy in identifying critical defects with
the system. This accuracy is necessary for promptly detect
potential hazards and preventing the occurrence of seri
accidents.
Hence, by the aforementioned clas Thence, by the atorementioned classification criteria, a

rel dataset comprising critical defects of connection

del, as illustrated in TABLE VI.

The YOLOv8 model, which had performed relatively well

comprehensive defec

oresented in Table VII.		The YOLOv8 model, which had performed relatively well in comprehensive defect-type detection, was selected to conduct comparison experiments with YOLOv7 and the improved model YOLOv7 m. The experimental results are TABLE VI. NUMBER OF EXPANDED CLASSIFICATIONS FOR SPECIFIC		
		DATASETS.		
Typology	Severe defects	High number of defects	Total	
Training sets	457	366	823	
Validation sets	53	47	100	
Test sets	59	42	101	
Total	569	455	1024	
		TABLE VII. COMPARATIVE EXPERIMENTS ON ATTENTIONAL MECHANISMS.		
Arithmetic	Precision $(\%)$	$Recall(\%)$	mAP@0.5(%)	
YOLOv7	86.9	90.0	88.2	

IAENG International Journal of Computer Scien
points. This suggests that the enhanced model offers notable
improvements in performance for critical defect detection,
particularly in terms of accuracy.
The precision resul **IAENG International Journal of Computer Sci**
points. This suggests that the enhanced model offers notable
improvements in performance for critical defect detection,
particularly in terms of accuracy.
The precision results **IAENG International Jou**
points. This suggests that the enhanced model offers notable
improvements in performance for critical defect detection,
particularly in terms of accuracy.
The precision results are visually depict **IAENG Intermost SERV INTERENT SERVIET SURFASHED SERVIET SURFASHED SURFASHED SURFASHED SURFASHED SURFASHED SURFASHED SURFASHED SURFASHED SURF**

Ferrator of Fig. 15. Comparison chart of precision results.

Ferrator of the connection buckles in connection buckles of the connection buckles of the connection buckles of the connection buckles of the connection buckles 0.2
 $\begin{bmatrix}\n\frac{1}{250} & \frac{1}{250} & \frac{1}{300} & \frac{1}{300} \\
\frac{1}{250} & \frac{1}{300} & \frac{1}{250} & \frac{1}{300} \\
\frac{1}{250} & \frac{1}{250} & \frac{1}{300} & \frac{1}{250} & \frac{1}{250} \\
\frac{1}{250} & \frac{1}{300} & \frac{1}{250} & \frac{1}{300} & \frac{1}{250} & \frac{1}{250} \\
\frac{1}{250} & \frac{1}{250$ are atter of the model, as shown in Fig. 16 below.

and the effects in connection buckles
 $\frac{1}{250}$ and $\frac{1}{250}$ and $\frac{1}{250}$ types of defects with heighte

Epoch

Fig. 15. Comparison chart of precision results.
 ⁸

⁸

⁸

⁸

⁸

⁰ ⁵⁰ ¹⁰⁰ ¹⁵⁰ ²⁰⁰ ²⁵⁰ ²⁵⁰ ³⁰⁰

⁸ Epoch

⁸ Excrementation of Fig. 15 reveals that the model tends

⁸ connectin Expected to the model of the model as shown in Fig. 16 below.

Fig. 15. Comparison chart of precision results.

Expedition of Fig. 15 reveals that the model tends and increased precision for Fig. 15 reveals that the model

Superior detection capabilities across all defect the superior detection capabilities across all defect categories, with the enhanced algorithm discussed in this study of large continuous converting the enhanced algorithm **Particularly Controlled Solution**

Particular of critical defect detection results.

Fig. 16. Visualization of critical defect detection results.

The enhanced algorithm discussed in this study

of large continuous convey 159 (2017) 223-236. https://doi.org/ in 1.1 Pan. Research on online skell

Fig. 16. Visualization of critical defect detection results.

The enhanced algorithm discussed in this study

of Paragon of intelligent conveyor b Fig. 16. Visualization of critical defect detection results.

The enhanced algorithm discussed in this study

of large continuous convey

The enhanced algorithm discussed in this study

on for critical defects. Furthermore Fig. 16. Visualization of critical defect detection results.

The enhanced algorithm discussed in this study

of the properties a consistent detection accuracy exceeding 90%

for critical defects. Furthermore, it reliably

THENG International Journal of Computer Science

The precision results the enhanced model offers notable

The precision results are for critical defect detection,

The precision results are visually depicted in Fig. 15 **The Science**

V. CONCLUSION AND FUTURE WORK

on buckles are widely used in joining

1 transportation belts, and it is essential to

dentify any defects they may have. Despite the I **of Computer Science**
V. CONCLUSION AND FUTURE WORK
Connection buckles are widely used in joining
derground transportation belts, and it is essential to
curately identify any defects they may have. Despite the
portance o **nal of Computer Science**

V. CONCLUSION AND FUTURE WORK

Connection buckles are widely used in joining

underground transportation belts, and it is essential to

accurately identify any defects they may have. Despite the
 and of Computer Science

V. CONCLUSION AND FUTURE WORK

Connection buckles are widely used in joining

underground transportation belts, and it is essential to

accurately identify any defects they may have. Despite the
 implancial of Computer Science

V. CONCLUSION AND FUTURE WORK

Connection buckles are widely used in joining

underground transportation belts, and it is essential to

accurately identify any defects they may have. Despi **nal of Computer Science**

V. CONCLUSION AND FUTURE WORK

Connection buckles are widely used in joining

underground transportation belts, and it is essential to

accurately identify any defects they may have. Despite the **nal of Computer Science**

V. CONCLUSION AND FUTURE WORK

Connection buckles are widely used in joining

underground transportation belts, and it is essential to

accurately identify any defects they may have. Despite the
 IV. CONCLUSION AND FUTURE WORK

Connection buckles are widely used in jounderground transportation belts, and it is essentificated accurately identify any defects they may have. Despite importance of this issue, there is **If of Computer Science**

V. CONCLUSION AND FUTURE WORK

Connection buckles are widely used in joining

derground transportation belts, and it is essential to

curately identify any defects they may have. Despite the

port V. CONCLUSION AND FUTURE WORK
Connection buckles are widely used in joining
underground transportation belts, and it is essential to
accurately identify any defects they may have. Despite the
importance of this issue, the V. CONCLUSION AND FUTURE WORK
Connection buckles are widely used in joining
underground transportation belts, and it is essential to
accurately identify any defects they may have. Despite the
importance of this issue, the V. CONCLUSION AND FUTURE WORK
Connection buckles are widely used in joining
underground transportation belts, and it is essential to
accurately identify any defects they may have. Despite the
importance of this issue, the V. CONCLUSION AND FUTURE WORK

Connection buckles are widely used in joining

underground transportation belts, and it is essential to

accurately identify any defects they may have. Despite the

importance of this issue, derground transportation belts, and it is essential to
curately identify any defects they may have. Despite the
portance of this issue, there is a lack of research on it at
th national and global levels. This study aims t

Specifically: accurately identify any defects they may have. Despite the
importance of this issue, there is a lack of research on it at
both national and global levels. This study aims to address
this gap by proposing an improved defect

importance of this issue, there is a lack of research on it at
both national and global levels. This study aims to address
this gap by proposing an improved defect detection model
and outlining its advantages.
The enhanced both national and global levels. This study aims to address
this gap by proposing an improved defect detection model
and outlining its advantages.
The enhanced YOLOv7_m model demonstrates strong
performance in detecting bo this gap by proposing an improved defect detection model
and outlining its advantages.
The enhanced YOLOv7_m model demonstrates strong
performance in detecting both complex and critical defects in
connection buckles. This and outlining its advantages.

The enhanced YOLOv7_m model demonstrates strong

performance in detecting both complex and critical defects in

connection buckles. This model showcases clear detection

superiority compared The enhanced YOLOv7_m model demonstrate
performance in detecting both complex and critical d
connection buckles. This model showcases clear c
superiority compared to the original network mo
prevailing defect detection mode rformance in detecting both complex and critical defects in
nnection buckles. This model showcases clear detection
periority compared to the original network model and
evailing defect detection models currently in use.
eci connection buckles. This model showcases clear detection
superiority compared to the original network model and
prevailing defect detection models currently in use.
Specifically:
1. The enhanced YOLOv7_m model demonstrates superiority compared to the original network model and
prevailing defect detection models currently in use.
Specifically:
1. The enhanced YOLOv7_m model demonstrates
significant efficacy in identifying various types of com

prevailing defect detection models currently in use.
Specifically:
1. The enhanced YOLOv7_m model demonstrates
significant efficacy in identifying various types of complex
defects in connection buckles. This model exhibits Specifically:

1. The enhanced YOLOv7_m model demonstrates

significant efficacy in identifying various types of complex

defects in connection buckles. This model exhibits superior

capabilities in accurately recognizing 1. The enhanced YOLOv7_m model demonstrates
significant efficacy in identifying various types of complex
defects in connection buckles. This model exhibits superior
capabilities in accurately recognizing and detecting var settings. fects in connection buckles. This model exhibits superior
pabilities in accurately recognizing and detecting various
poses of defects with heightened efficiency, thereby largely
filling the industry's overarching criteria capabilities in accurately recognizing and detecting various
types of defects with heightened efficiency, thereby largely
fulfilling the industry's overarching criteria for connecting
buckle defect detection.
2. The enhanc types of defects with heightened efficiency, thereby largely
fulfilling the industry's overarching criteria for connecting
buckle defect detection.
2. The enhanced model demonstrates improved efficacy
and increased precisi fulfilling the industry's overarching criteria for connecting
buckle defect detection.
2. The enhanced model demonstrates improved efficacy
and increased precision in identifying critical defects in
connecting buckles. Thi buckle defect detection.

2. The enhanced model demonstrates improved efficacy

and increased precision in identifying critical defects in

connecting buckles. This outcome serves to validate the

viability of the enhanced 2. The enhanced model demonstrates im

and increased precision in identifying crit

connecting buckles. This outcome serves

viability of the enhanced model and establish

and technological foundation for the future

of de

or decet detection in connection buckles whilm industrial
settings.
In future work, we will consider incorporating
self-learning, semi-supervised, or unsupervised models based
on the enhanced model to decrease the need for ngs.

I future work, we will consider incorporating

learning, semi-supervised, or unsupervised models based

the enhanced model to decrease the need for manual

ling, increase automation, and facilitate the application of future work, we will consider incorporating
learning, semi-supervised, or unsupervised models based
he enhanced model to decrease the need for manual
ling, increase automation, and facilitate the application of
improved mo self-learning, semi-supervised, or unsupervised models based
on the enhanced model to decrease the need for manual
labeling, increase automation, and facilitate the application of
the improved model to other types of conne rearining, seint supervised, or unsupervised models of asset
the enhanced model to decrease the need for manual
ling, increase automation, and facilitate the application of
improved model to other types of connection buckl ne enhanced model to decrease the need for manual

ling, increase automation, and facilitate the application of

improved model to other types of connection buckle

ct detection.
 REFERENCES

Peng Zhang, Shaochuan Xu, an [3] Interests automation, and facilitate the application of
the improved model to other types of connection buckle
defect detection.
The serves of connection buckle
defect detection.
The serves of summer and Design
of Belt

REFERENCES

-
-
- improved model to other types of connection buckle
ct detection.
REFERENCES
Peng Zhang, Shaochuan Xu, and Minghao Ma, "Research and Design
of Belt Deviation Detection System Based on Single-side Rollers,"
K. Chababne, et a The Costal Conter Costal Conter Costal Content Costal Content Costal Content Costal Content Costal Content Costa

Peng Zhang, Shaochuan Xu, and Minghao Ma, "Research and Design

of Belt Deviation Detection System Based on REFERENCES

[1] Peng Zhang, Shaochuan Xu, and Minghao Ma, "Research and Design

of Belt Deviation Detection System Based on Single-side Rollers,"

Engineering Letters, vol. 32, no. 4, pp871-879, 2024

[2] K. Chaabane, et a REFERENCES

Peng Zhang, Shaochuan Xu, and Minghao Ma, "Research and Design

of Belt Deviation Detection System Based on Single-side Rollers,"

Engineering Letters, vol. 32, no. 4, pp871-879, 2024

K. Chaabane, et al. Integ
- 2012,5-6.
Y. Pang, G. Lodewijks. A novel embedded conductive detection syste
- [1] Peng Zhang, Shaochuan Xu, and Minghao Ma, "Research and Design
of Belt Deviation Detection System Based on Single-side Rollers,"
Engineering Letters, vol. 32, no. 4, pp871-879, 2024
[2] K. Chaabane, et al. Integrated Peng Zhang, Shaochuan Xu, and Minghao Ma, "Research and Design
of Belt Deviation Detection System Based on Single-side Rollers,"
Engineering Letters, vol. 32, no. 4, pp871-879, 2024
K. Chaabane, et al. Integrated imperfect of Belt Deviation Detection System Based on Single-side Rollers,"
Engineering Letters, vol. 32, no. 4, pp871-879, 2024

K. Chaabane, et al. Integrated imperfect multimission selective

maintenance and repairpersons assignm
- Engmeering Letters, vol. 32, no. 4, pp871-879, 2024

K. Chaabane, et al. Integrated imperfect multimission selective

maintenance and repairpersons assignment problem, Reliab. Eng. Syst.

Saf. 199 (2020). https://doi.org/1 [2] K. Chaabane, et al. Integrated imperfect multimission selective
maintenance and repairpersons assignment problem, Reliab. Eng. Syst.
Saf. 199 (2020). https://doi.org/10.1016/j.ress.2020.106895
S. Jocelyn, et al. Appli maintenance and repairpersions assignment problem, Reliab. Eng. Syst.
Saf. 199 (2020). https://doi.org/10.1016/j.ress.2020.106895
S. Jocelyn, et al. Application of logical analysis of data to machinery
related accident pre Saf. 199 (2020). https://doi.org/10.1016/j.ress.2020.106895
S. Jocelyn, et al. Application of logical analysis of data to machinery
related accident prevention based on scarce data, Reliab. Eng. Syst. Saf.
159 (2017) 223–2 https://doi.org/10.1109/cvpr.2014.81
Liu. W, et al. SSD: Single Shot MultiBox Detector, vol. 9905.2016, pp related accident prevention based on scarce data, Reliab. Eng. Syst. Saf.

159 (2017) 223–236. https://doi.org/10.1016/j.ress.2016.11.015

14J I. J. Pan. Research on online skeleton detection and fault identification

of l [4] H.J. Pan. Research on online skeleton detection and fault identification
of large continuous conveyor belts[D].ShenYang: Dongbei University,
2012,5-6.
If Y. Pang, G. Lodewijks. A novel embedded conductive detection sys of large continuous conveyor belts[D].ShenYang: Dongbei University,
2012,5-6.

[5] Y. Pang, G. Lodewijks. A novel embedded conductive detection syste

-m for intelligent conveyor belt monitoring, in 2006 IEEE Internation
 2012,5-6.

Y. Pang, G. Lodewijks. A novel embedded conductive detection syste

Y. Pang, G. Lodewijks. A novel embedded conductive detection syste

am for intelligent conveyor belt monitoring, in 2006 IEEE Internation

al c [5] Y. Pang, G. Lodewijks. A novel embedded conductive detection syste

- in for intelligent conveyor belt monitoring, in 2006 IEEE Internation

al conference on service operations and logistics, and informatics, Sha

ngha -m for intelligent conveyor belt monitoring, in 2006 IEEE Internation
al conference on service operations and logistics, and informatics, Sha
eq. 2006, pp. 803-808. https://doi.org/10.1109/cvili-02006.328958
G. Ross, et al al conference on service operations and logistics, and informatics, Sha
nghai, 2006, pp. 803–808. https://doi.org/10.1109/soli.2006.328958
G. Ross, et al. Rich feature hierarchies for accurate object detection and
semantic nghai, 2006, pp. 803–808. https://doi.org/10.1109/soli.2006.328958
G. Ross, et al. Rich feature hierarchies for accurate object detection and
semantic segmentation. Proceedings of IEEE conference on computer
vision and pat
-
- 21-37
X. Zhou, D. Wang, and P. Kra henbu hl. Objects as Points, 2019.
-
- [6] G. Ross, et al. Rich feature hierarchies for accurate object detection and
semantic segmentation. Proceedings of IEEE conference on computer
vision and pattern recognition (CVPR), 2014: pp. 580-587.
https://doi.org/10. semantic segmentation. Proceedings of IEEE conference on computer
vision and pattern recognition (CVPR), 2014: pp. 580-587.
ILiu. W, et al. SSD: Single Shot MultiBox Detector, vol. 9905.2016, pp
21-37
X. Zhou, D. Wang, and
- 2022
- **IAENG International Journal of Compute**

[12] Tianzhen Liu, Yingchun Yuan, Guifa Teng, and Xi Meng, "Improved

Deep Convolutional Neural Network-Based Method for Detecting

Winter Jujube Fruit in Orchards," Engineering Le **IAENG International Journal of Compute**
Tianzhen Liu, Yingchun Yuan, Guifa Teng, and Xi Meng, "Improved
Deep Convolutional Neural Network-Based Method for Detecting
Winter Jujube Frui in Orchards," Engineering Letters, vo **IAENG International Journal of Computer Scie**
Tianzhen Liu, Yingchun Yuan, Guifa Teng, and Xi Meng, "Improved
Deep Convolutional Neural Network-Based Method for Detecting
Winter Jujube Fruit in Orchards," Engineering Lett **IAENG Inte**
Tianzhen Liu, Yingchun Yuan, Guifa Teng, and X
Deep Convolutional Neural Network-Based Met
Winter Jujube Fruit in Orchards," Engineering Let
pp569-578, 2024
Yongzhong Fu, Liang Qiu, Xiao Kong, and
Learning-Bas **IAENG International Journal of Computer S**

[12] Tianzhen Liu, Yingchun Yuan, Guifa Teng, and Xi Meng, "Improved

Deep Convolutional Neural Network-Based Method for Detecting

Winter Jujube Fruit in Orchards," Engineering **IAENG International Journal of Computer S**

Tianzhen Liu, Yingchun Yuan, Guifa Teng, and Xi Meng, "Improved

Deep Convolutional Neural Network-Based Method for Detecting

Winter Jujube Fruit in Orchards," Engineering Lett **IAENG International Journal of Compute:**
Tianzhen Liu, Yingchun Yuan, Guifa Teng, and Xi Meng, "Improved
Deep Convolutional Neural Network-Based Method for Detecting
Winter Jujube Fruit in Orchards," Engineering Letters, **IAENG International Journal of Computer Sc**

[12] Tianzhen Liu, Yingchun Yuan, Guifa Teng, and Xi Meng, "Improved

Deep Convolutional Neural Network-Based Method for Detecting

Winter Jujube Fruit in Orchards," Engineerin **IAENG International Journal of Compu**

Tianzhen Liu, Yingchun Yuan, Guifa Teng, and Xi Meng, "Improved

Deep Convolutional Neural Network-Based Method for Detecting

Winter Jujube Fruit in Orchards," Engineering Letters, Tianzhen Liu, Yingchun Yuan, Guifa Teng, and Xi Meng, "Improved
Deep Convolutional Neural Network-Based Method for Detecting
Winter Jujube Fruit in Orchards," Engineering Letters, vol. 32, no. 3,
pp569-578, 2024
Yongzhong Tianzhen Liu, Yingchun Yuan, Guifa Teng, and Xi Meng
Deep Convolutional Neural Network-Based Method fo
Winter Jujube Fruit in Orchards," Engineering Letters, vo
pp569-578, 2024
Yongzhong Fu, Liang Qiu, Xiao Kong, and Haifu [12] Tianzhen Liu, Yingchun Yuan, Guifa Teng, and Xi Meng, "Improved

Deep Convolutional Neural Network-Based Method for Detecting

Winter Jujub Fruit in Orchards," Engineering Letters, vol. 32, no. 3,

13) Yongzhong Fu, L Tianzhen Liu, Yingchun Yuan, Guifa Teng, and Xi Meng, "Improved
Deep Convolutional Neural Network-Based Method for Detecting
Winter Jujube Fruit in Orchards," Engineering Letters, vol. 32, no. 3,
Pongzhong Fu, Liang Qiu, X
-
- Tranzhen Luu, Yingchun Yuan, Guita Teng, and X
Deep Convolutional Neural Network-Based Met
Winter Jujube Fruit in Orchards," Engineering Let
pp569-578, 2024
Vongzhong Fu, Liang Qiu, Xiao Kong, and
Yongzhong Fu, Liang Qiu, Deep Convolutional Neural Network-Based Method for Detecting
Winter Jujube Fruit in Orchards," Engineering Letters, vol. 32, no. 3,
pp569-578, 2024
13] Yongzhong Fu, Liang Qiu, Xiao Kong, and Haifu Xu, "Deep
Learning-Based Winter Juyube Fruit in Orchards," Engineering Letters, vol. 32, no. 3,

pp569-578, 2024

Yongzhong Fu, Liang Qiu, Xiao Kong, and Haifu Xu, "Deep

Learning-Based Online Surface Defect Detection Method for Door

Trim Panel," pp569-578, 2024

Yongzhong Fu, Liang Qiu, Xiao Kong, and Haifu Xu, "Deep

Learning-Based Online Surface Defect Detection Method for Door

Trim Panel," Engineering Letters, vol. 32, no. 5, pp939-948, 2024

Yu Zhang, Ming Ma
-
-
- [13]Yongzhong Fu, Liang Qiu, Xiao Kong, and Haifu Xu, "Deep

Learning-Based Online Surface Defect Detection Method for Door

Trim Panel," Engineering Letters, vol. 32, no. 5, pp939-948, 2024

[14] Yu Zhang, Ming Ma, Zhong Learning-Based Online Surface Defect Detection Method for Door

Frim Panel, "Enginering Letters, vol. 32, no. 5, pp939-948, 2024

Yu Zhang, Ming Ma, Zhongxiang Wang, Jing Li, and Yan Sun,

POD-YOLO Object Detection Model B Trim Panel," Engineering Letters, vol. 32, no. 5, pp939-948, 2024

Yu Zhang, Ming Ma, Zhongxiang Wang, Jing Li, and Yan Sun,

"POD-YOLO Object Detection Model Based on Bi-directional

Dynamic Cross-level Pyramid Network," 918951 "POD-YOLO Object Detection Model Based on Bi-directional

Dynamic Cross-level Pyramid Network," Engineering Letters, vol. 32,

no. 5, pp995-1003, 2024

[15] Shiqin Li, and Weisheng Liu, "Small Target Detection Model in Ae Dynamic Cross-level Pyramid Network," Engineering Letters, vol. 32,

Shiqin Li, and Weisheng Liu, "Small Target Detection Model in Aerial

Images Based on YOLOv7X+," Engineering Letters, vol. 32, no. 2,

pp436-443, 2024

H no. 5, pp995-1003, 2024
Shiqin Li, and Weisheng Liu, "Small Target Detection Model in Aerial
Shiqin Li, and Weisheng Liu, "Small Target Detection Model in Aerial
H. Lu, Y. Li, M. Chen, H. Kim, S. Serikawa, Brain intelligen Shiqin Li, and Weisheng Liu, "Small Target Detection Model in Aerial
Images Based on YOLOv7X+," Engineering Letters, vol. 32, no. 2,
pp436-443, 2024
H. Lu, Y. Li, M. Chen, H. Kim, S. Serikawa, Brain intelligence: go
beyond Images Based on YOLOV/X+," Engineering Letters, vol. 32, no. 2, pp436-443, 2024

[16] H. Lu, Y. Li, M. Chen, H. Kim, S. Serikawa, Brain intelligence: go

beyond artificial intelligence, Mobile Netw. Appl. 23 (2) (2018)

3 pp436-443, 2024

H. Lu, Y. Li, M. Chen, H. Kim, S. Serikawa, Brain intelligence: go

Heyond artificial intelligence, Mobile Netw. Appl. 23 (2) (2018)

368–375. https://doi.org/10.1007/s11036-017-0932-8

Z. Zhou, X. Chen, E H. Lu, Y. Li, M. Chen, H. Kim, S. Serikawa, Brain intelligence: go
beyond artificial intelligence, Mobile Netw. Appl. 23 (2) (2018)
368–375. https://doi.org/10.1007/s11036-017-0932-8
Z. Zhou, X. Chen, E. Li, L. Zeng, K. Lu beyond arthrical intelligence, Mobile Netw. Appl. 23 (2) (2018)
268–375. https://doi.org/10.1007/s11036-017-0932-8
2. Zhou, X. Chen, E. Li, L. Zeng, K. Luo, J. Zhang. Edge Intelligence:
Paving the last mile of artificial i 368–375. https://doi.org/10.1007/s11036-017-0932-8

[17] Z. Zhou, X. Chen, E. Li, L. Zeng, K. Luo, J. Zhang. Edge Intelligence:

Pavaig the last mile of artificial intelligence with edge computing, P I

-EEE 107 (8) (2019
-
- Z. Zhou, X. Chen, E. Li, L. Zeng, K. Luo, J. Zhang. Edge Intelligence:

Paving the last mile of artificial intelligence with edge computing, P I

PEE 107 (8) (2019) 1738–1762. https://doi.org/10.1109/iproc.2019.2

218951
 Paving the last mile of artificial intelligence with edge computing, P 1-
EEE 107 (8) (2019) 1738–1762. https://doi.org/10.1109/jproc.2019.2
218951
Win Wen, Yi Yao, Ying Cai, Zixing Zhao, Tianjiao Chen, Ziyu Zeng,
Zhen Tan FEE 107 (8) (2019) 1738-1762. https://doi.org/10.1109/jproc.2019.2

18 J. Sin Wen, Yi Yao, Ying Cai, Zixing Zhao, Tianjiao Chen, Ziyu Zeng,

Zhen Tang, "A Lightweight ST-YOLO Based Model for Detection of

Tea Bud in Unstr 918951

Xin Wen, Yi Yao, Ying Cai, Zixing Zhao, Tianjiao Chen, Ziyu Zeng,

Xin Wen, Yi Yao, Ying Cai, Zixing Zhao, Tianjiao Chen, Ziyu Zeng,

Zhen Tang, "A Lightweight ST-YOLO Based Model for Detection of

Tea Bud in Unstr Xin Wen, Yi Yao, Ying Cai, Zixing Zhao, Tianjiao Chen, Ziyu Zeng,
Zhen Tang, "A Lightweight ST-YOLO Based Model for Detection of
Tea Bud in Unstructured Natural Environments, "IAENG International
Journal of Applied Mathema ZhenTang, "A Lightweight ST-YOLO Based Model for Detection of

Tea Bud in Unstructured Natural Environments, "IAENG International

Iournal of Applied Mathematics, vol. 54, no. 3, pp342-349, 2024

[19] X. Y. Dai, et al. Dy Journal of Applied Mathematics, vol. 54, no. 3, pp342-349, 2024

[19] X. Y. Dai, et al. Dynamic Head: Unifying Object Dectric Dietas with

Attentions; Proceedings of the IEEE/CVF conference on computer

vision and pattern X. Y. Dai, et al. Dynamic Head: Unitying Object Detection Heads with
Attentions; Proceedings of the IEEE/CVF conference on computer
vision and pattern recognition (CVPR), Elect Network, F Jun 19-25,
2021[C].2021. https://d
-
-
- https://doi.org/10.48550/arXiv.1804.02767
-
- Attentions; Proceedings of the IEEE/CVF conference on computer
vision and pattern recognition (CVPR), Electr Network, F Jun 19-25,
2021 [C], 2021. https://doi.org/10.1109/cvpr46437.2021.00729
[20] HU J, SHEN L, ALBANIE S, vision and pattern recognition (CVPR), Electr Network, F Jun 19-25,
2021 [CJ2O21.https://do.iorg/10.1109/cvpr44437.2021.00729
HU J, SHEN L, ALBANIE S, et al. Squeeze-and-Excitation Networks
[J].IEEE transactions on patter 2021[C]:2021. https://doi.org/10.1109/cvpr46437.2021.00729

HU J, SHEN L, ALBANIE S, et al. Squeeze-and-Excitation Networks

HJ.EEE transactions on pattern analysis and machine intelligence, 20

20, 42(8): 2011-23. https: https://doi.org/10.23919/eusipco54536.2021.9616026
- [J].IEEE transactions on pattern analysis and machine intelligence, 20

20, 42(8): 2011-23. https://doi.org/10.1109/covpr.2018.00745

[21] J. Redmon, A. Farhadi. Yolo9000: Better, faster, stronger, in IEEE

conference on 20, 42(8): 2011-23. https://doi.org/10.1109/cvpr.2018.00745

J. Redmon, A. Farhadi. Yolo900: Better, faster, stronger, in IEEE

conference on computer vision & pattern recognition, 2017, pp.

6517–6525. https://doi.org/10 J. Redmon, A. Farhadi. Yolo9000: Better, faster, stronger, in IEEE

cofference on computer vision & pattern recognition, 2017, pp.

6517–6525. https://doi.org/10.48550/arXiv.1612.08242

A. F. Joseph Redmon. Yolov3: An incr https://doi.org/10.1109/cvpr46437.2021.01284
[26] C. Y. Wang, A. Bochkovskiy, H. Liao, Yolov7: Trainable bag-of-free 6517–6525. https://doi.org/10.48550/arXiv.1612.08242

[22] A. F. Joseph Redmon. Yolov3: An incremental improvement.

https://doi.org/10.48550/arXiv.1804.02767

[23] Bochkovskiy, C. Y. Wang. Yolov4: Optimal speed and accur A. F. Joseph Redmon. Yolov3: An incremental improvement.

https://doi.org/10.48550/arXiv.1804.02767

Bochkovskiy, C. Y. Wang. Yolov4: Optimal speed and accuracy of

object detection. https://doi.org/10.48550/arXiv.2004.109 [23] Bochkovsky, C. Y. Wang. Yolov4: Optimal speed and accuracy of object detection. https://doi.org/10.48550/arXiv.2004.10934
[24] W. S. Mseddi, R. Ghali, M. Jmal, R. Attia. Fire detection and segmentation using yolov5 a object detection. https://doi.org/10.48550/arXiv.2004.10934
W. S. Mseddi, R. Ghali, M. Jmal, R. Attia. Fire detection and
segmentation using yolov5 and u-net, in 2021 29th European Signal
Processing Conference (EUSIPCO), 2 segmentation using yolov5 and u-net, in 2021 29th European Signal

Processing Conference (EUSIPCO), 2021, pp. 741–745.

https://doi.org/10.23919/eusipeoc54536.2021.9616026

[25] Q. Chen, Y. Wang, T. Yang, X. Zhang, J. Chen Processing Conference (EUSIPCO), 2021, pp. 741–745.
https://doi.org/10.23919/eusipco54536.2021.9616026
Q. Chen, Y. Wang, T. Yang, X. Zhang, J. Cheng, J. Sun. You only look
at one-level feature, in 2021 IEEE/CVF conference
- org/10.1109/cvpr52729.2023.00721
- 62
- https://doi.org/10.3390/sym13040623
- [25] Q. Chen, Y. Wang, T. Yang, X. Zhang, J. Cheng, J. Sun. You only look

at one-level facture, in 2021 IEEC/CVF conference on computer vision

and pattern recognition (CVPR), 2021, pp. 13034–13043.

https://doi.org/10.11 at one-level feature, in 2021 IEEE/CVF conference on computer vision
and pattern recognition (CVPR), 2021, pp. 13034–13043.
https://doi.org/10.1109/cvpr46437.2021.01284
C. Y. Wang, A. Bochkovskiy, H. Liao, Yolov7: Trainabl and pattern recognition (CVPR), 2021, pp. 13034–13043.
https://doi.org/10.1109/cvpr46437.2021.01284
C. Y. Wang, A. Bochkovskiy, H. Liao, Yolov7: Trainable bag-of-free-
bies sets new state-of-the-art for real-time object de https://doi.org/10.48550/arXiv.2103.02907
[30] Q. L. Zhang, Y. B. Yang. SA-Net: Shuffle Attention for Deep [26]C. Y. Wang, A. Bochkovskiy, H. Liao, Yolov7: Trainable bag-of-free

-bies sets new state-of-the-art for eral-time object detectors. https://doi.

org/10.1109/cvpr52729-2023.00721

[27] Siliang Ma, Y. Xu. MPDIoU: A Los -bies sets new state-of-the-art for real-time object detectors. https://doi.

org/10.1109/crypr52729.2023.00721

Siliang Ma, Y. Xu. MPDIoU: A Loss for Efficient and Accurate Boun

-ding Box Regression. 2011. https://doi.or [27] Siliang Ma, Y. Xu. MPDIoU: A Loss for Efficient and Accurate Boundary and Box Regression. 2011. https://doi.org/10.48550/arXiv.2307.076 [28] H. X. Fu , G. Q. Song, Y. C Wang. Improved YOLOv4 marine target detection c
- https://doi.org/10.1109/icassp39728.2021.9414568
[31] S. Q. Ren, K. M. He, et al. Faster R-CNN: Towards real-time object.
-