



Deep Learning-Based Damage Detection of Mining Conveyor Belts

Mr. S.Duari*, Mr. K.Rajkumar¹

* - Corresponding author: Assistant Professor, Department of Mechanical Engineering,

1- ME Industrial Safety Engineering, KSR College of Engineering (Autonomous), Tiruchengode, Tamil Nadu, India

ABSTRACT

The mining conveyor belt is a crucial component of the coal mine belt conveyor system, responsible for transporting materials and transmitting power. Due to the harsh working conditions, these belts are prone to damage. To address this issue, we reclassified and defined various types of conveyor belt damage and created a specialized dataset for this purpose. We then proposed a novel detection method capable of simultaneously identifying multiple faults using an improved YOLOv3 algorithm.

In this enhanced algorithm, Efficient Net replaces Darknet53 as the backbone feature extraction network, achieving a balance between network depth, width, and image resolution to enhance accuracy within limited computing resources. Experimental results demonstrate that our improved algorithm excels in both detection speed and accuracy, achieving a speed of 42 FPS and a mean average precision of 97.26%. Compared to the original YOLOv3 algorithm, our method increases accuracy by 10.4% and speed by 45.9%, offering innovative solutions for ensuring the safe and stable operation of conveyor belts.

Keywords:

Belt conveyor, Conveyor belt, Deep learning, Machine vision, Damage detection.

1. Introduction

As one of the most crucial components in the continuous transportation of bulk materials, the belt conveyor is evolving towards longer distances, higher speeds, larger volumes, and increased intelligence. The term "intelligence" refers to the conveyor's ability to achieve self-awareness, independent decision-making, and self-learning by utilizing various sensing devices such as optical cameras, infrared cameras, pickups, and vibration sensors. These devices collect real-time operational data, which is then analyzed and processed via cloud servers or edge computing devices to facilitate autonomous operation and unattended management of the conveyor.

The conveyor belt itself plays a vital role in material transport and power transmission, accounting for 30%–50% of the total conveyor cost. These belts are prone to longitudinal tearing, surface scratches, and other forms of damage due to issues like broken rollers or material jams. If such damage is not detected and addressed promptly, it can lead to more severe problems, including belt breakage. Currently, conveyor belt damage detection methods are either manual or non-destructive. Manual detection methods, such as observing surface bubbling or measuring length, are labour-intensive and outdated. Non-destructive testing (NDT) methods, including tear sensors, eddy current tests, weak magnetic tests, X-ray tests, and embedded conductive detection technology, offer real-time detection capabilities.

Advancements in computer technology have significantly improved the environment for digital image processing, making machine vision technology increasingly sophisticated and applicable to belt conveyors. This technology is used for

material classification, online ore composition analysis, and the identification of coal and gangue on conveyor belts. As conveyor systems become more intelligent, machine vision-based monitoring systems have been developed for tracking operational status, including deviation and tearing.

Early work in this field includes a 2003 study from Carnegie Mellon University, which developed a camera and image processing-based monitoring system for conveyor belt joints. Subsequent research has proposed various algorithms and techniques for detecting longitudinal tearing and deviations, using methods like fast image segmentation, line laser assistance, and dual-band infrared detection. These methods improve detection accuracy and reliability by analysing visual and thermal data to identify potential damage.

The core of conveyor belt damage detection is target detection, where deep learning now plays a dominant role. Deep learning bypasses the need for manual feature design and classifier selection, using hierarchical structures to map low-level to high-level semantic signals. This approach is well-suited to processing large volumes of image and video data, meeting the requirements for accuracy, efficiency, and intelligence.

In response to the growing need for intelligent belt conveyor systems, this paper proposes a deep learning-based damage detection method for mining conveyor belts. An improved YOLOv3 algorithm is introduced to detect various types of belt damage, with field experiments demonstrating enhanced accuracy and real-time performance. The main contributions of this paper include:

A comprehensive damage detection method that identifies multiple types of conveyor belt damage, not limited to belt tears.

A direct detection approach that does not rely on auxiliary devices or complex image processing techniques.

An improved YOLOv3 algorithm that optimizes the balance between speed and accuracy, is applicable to detecting other targets in different fields.

2. Methodology and Raw Data

2.1. Principle and Structure of the Improved Algorithm

Conveyor belt damage detection is fundamentally a target detection problem. Current supervised learning-based target detection methods fall into two main categories:

Two-stage target detection algorithms: These algorithms, such as the R-CNN series, generate candidate frames via regional proposal networks (RPN) and then use convolutional neural networks for classification and border refinement. Although they are more accurate, they are slower due to the numerous candidate frames, making them unsuitable for real-time applications.

Single-stage target detection algorithms: These algorithms, like SSD (Single Shot Multibox Detector) and YOLO (You Only Look Once), operate based on regression and are faster. Our research utilizes YOLOv3.

A target detection network consists of two parts: the backbone feature extraction network and the prediction network. The quality of features extracted by the feature extraction network directly influences the prediction accuracy. YOLOv3 uses Darknet53 as its backbone, which is designed based on the residual neural network (RNN) concept, composed of five residual blocks. Each block contains multiple residual units, solving the gradient explosion problem with deeper networks and improving feature extraction.

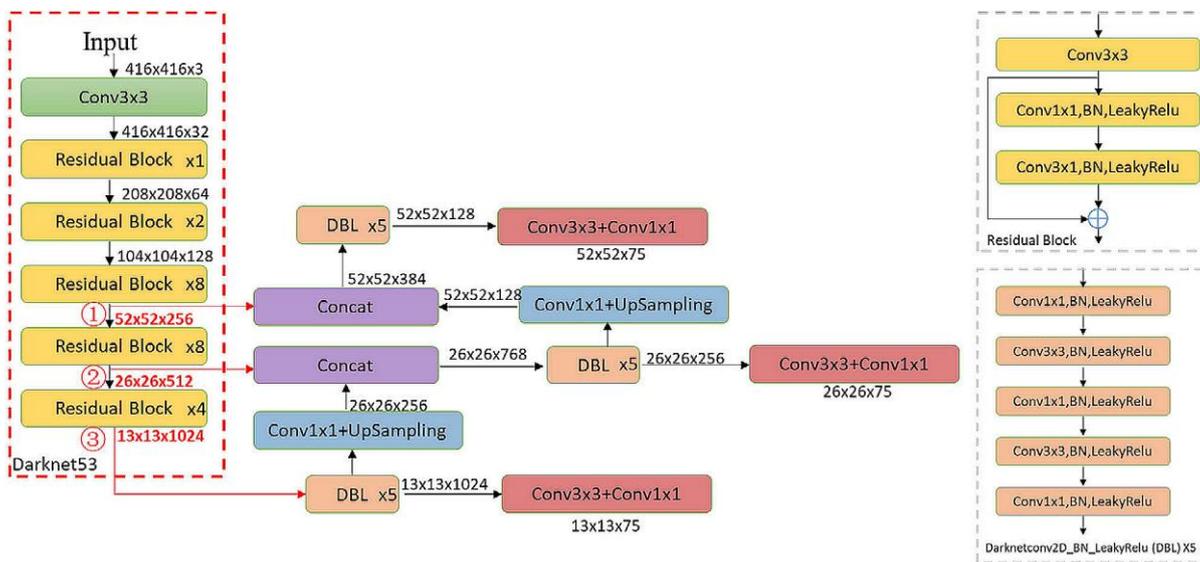


Fig.1 Structure of YOLOv3.

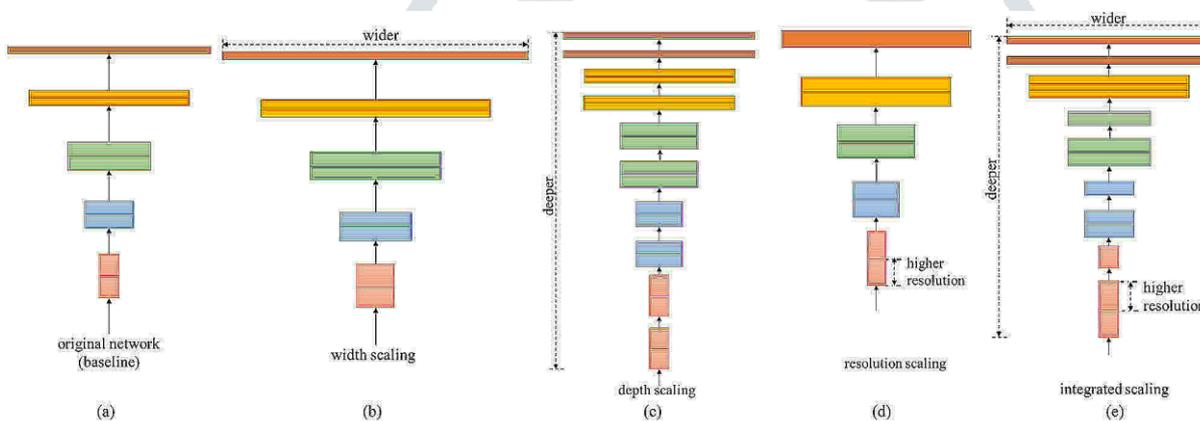


Fig. 2. Model scaling method.

YOLOv3 also incorporates the feature pyramid network (FPN) idea, using a multi-scale detection mechanism with three different-scale feature layers to enhance detection capability across various target sizes. This improves on YOLOv1 and YOLOv2, particularly in detecting small targets.

However, increasing the network depth, as seen in the transition from Darknet19 to Darknet53, can improve accuracy but also increases computational load, potentially reducing detection speed. Efficient Net proposes a balanced approach to network scaling by adjusting depth, width, and resolution to maximize performance within limited resources. This compound scaling method uses a set of parameters (α, β, γ) to balance these dimensions, guided by a user-specified coefficient (ϕ).

EfficientNet-B0 serves as the baseline network. By applying the compound scaling method, EfficientNet-B0 can be scaled up to EfficientNet-B7, enhancing feature extraction for YOLOv3's prediction network. This paper replaces Darknet53 with Efficient Net to leverage its superior feature extraction capabilities.

2.2. Definition of Conveyor Belt Damage Types

Conveyor belts, comprising upper and lower covering layers and a middle tensile layer, can be damaged by internal factors (e.g., material quality, vulcanization process) and external factors (e.g., operational environment). Damage types include surface wear, surface damage, tears, and breakdowns. Surface wear typically results from large coal lumps or stones obstructing chutes, leading to thinning rubber and exposed wire ropes. Tears can occur due to belt misalignment, metal objects, or large rocks, often due to improper operation. Surface damage includes bubbling or rubber detachment, linked

to belt processing quality. Long-distance conveyors with significant height differences are particularly prone to material impact-related breakdowns.

2.3. Preparation of Raw Data

We collected 3,000 images of conveyor belt damage through on-site visits and online searches, evenly distributed among the four damage types. A manually annotated dataset was created for algorithm testing. Training utilized stochastic gradient descent (SGD) to optimize the loss function over 30,000 iterations, with a batch size of 4, momentum of 0.9, and a decay coefficient of 0.0005. The initial learning rate was 0.001, reduced to 0.00001 after 20,000 iterations. Training data was augmented by altering image saturation, hue, value, and through random cropping and scaling.

2.4. Algorithm Running Environment

The neural network model training and testing were conducted on a computer with the following configuration:

OS	CPU	GPU	Tensorflow-gpu	Keras	Python
Windows10	E5-2620V3*2	RTX2060S	1.13.1	2.1.5	3.6.10

3. Results and Discussion

3.1. Performance Comparison of Multiple Algorithms

In multi-object classification tasks, mAP (mean Average Precision) [49] and FPS (Frames Per Second) are typically used to measure algorithm superiority. In this paper, we adopt these metrics. mAP, the mean of the AP for each class, evaluates the overall detection accuracy. FPS measures the processing speed.

To verify the performance of our improved algorithm, we tested various algorithms on the conveyor belt damage dataset using transfer learning, including Faster-RCNN, SSD, RFBnet, M2det, Yolov3, and Yolov4. Transfer learning significantly reduces the training time and computational resources required. The performance results are shown in Table 2.

In Table 2, Faster R-CNN's detection speed is 3.6 FPS, the slowest among the tested algorithms. Despite using the RPN to generate ROIs instead of selective search, its computation remains substantial compared to regression-based algorithms like Yolo and SSD. SSD, using multi-scale feature maps for detection, achieves 94.45% accuracy.

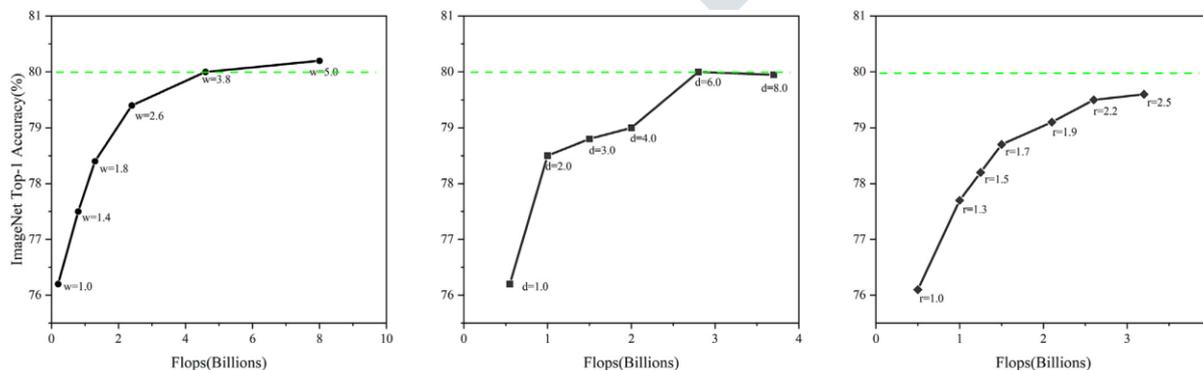


Fig. 3. Limitations of single-dimensional expansion

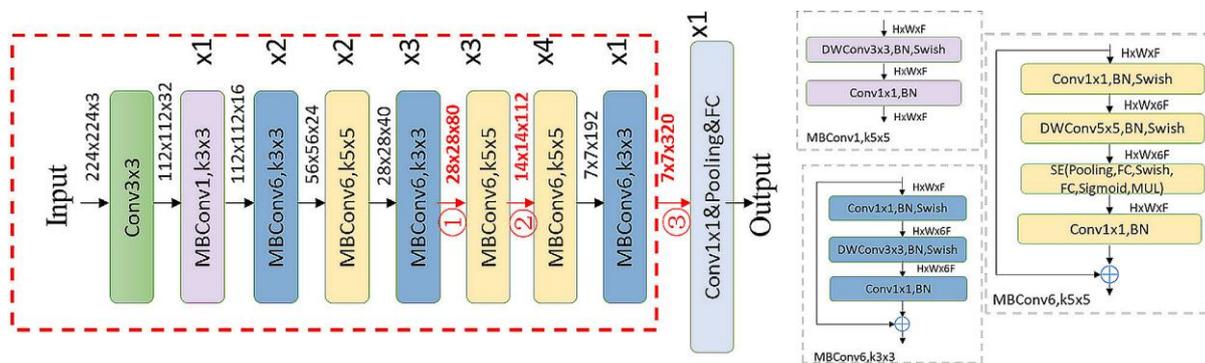


Fig. 4. Structure of EfficientNet-B0.

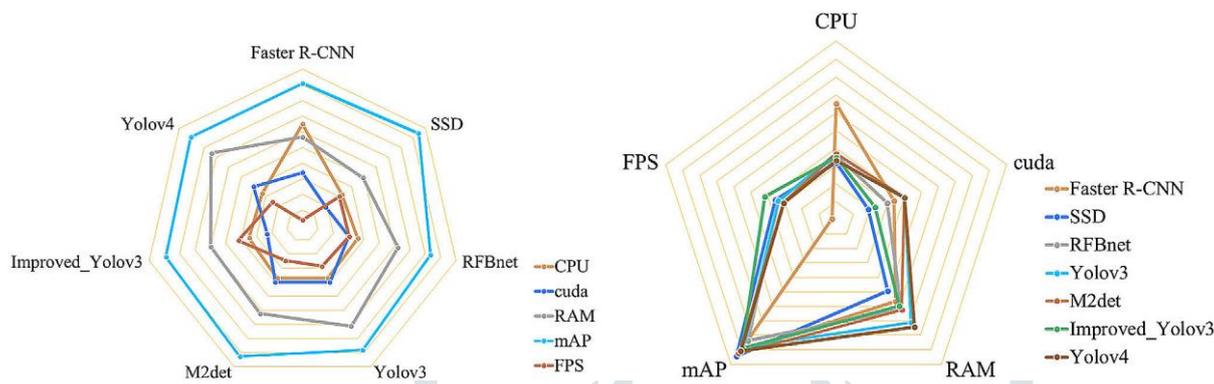


Fig. 5. The hardware usage of different algorithms

The improved algorithm, referred to as Improved-YOLOv3 in Table 2 (with EfficientNet-B0 as the backbone), achieves an average accuracy of 89.12% on the dataset, slightly higher than the original YOLOv3's 88.12%. This improvement is most notable in detecting tears. The improved algorithm significantly boosts prediction speed, increasing FPS from 28 to 42.

Efficient Net exists in eight variants (B0–B7), with B1–B7 expanding upon B0 by increasing the coefficient (ϕ). As (ϕ) increases, the network depth, width, and image resolution expand. We constrained $\alpha \cdot \beta^2 \cdot \gamma^2 \approx 2$ to ensure FLOPS increases by 2ϕ . Testing Efficient Net B0–B7 as Improved-YOLOv3's backbone showed the best speed-accuracy trade-off at 97.26% AP and 26.28 FPS, and 89.12% AP at 41.91 FPS. Due to graphics memory limitations, we encountered overflow issues with B5. The trend suggests further expansion would improve accuracy but slow detection speed.

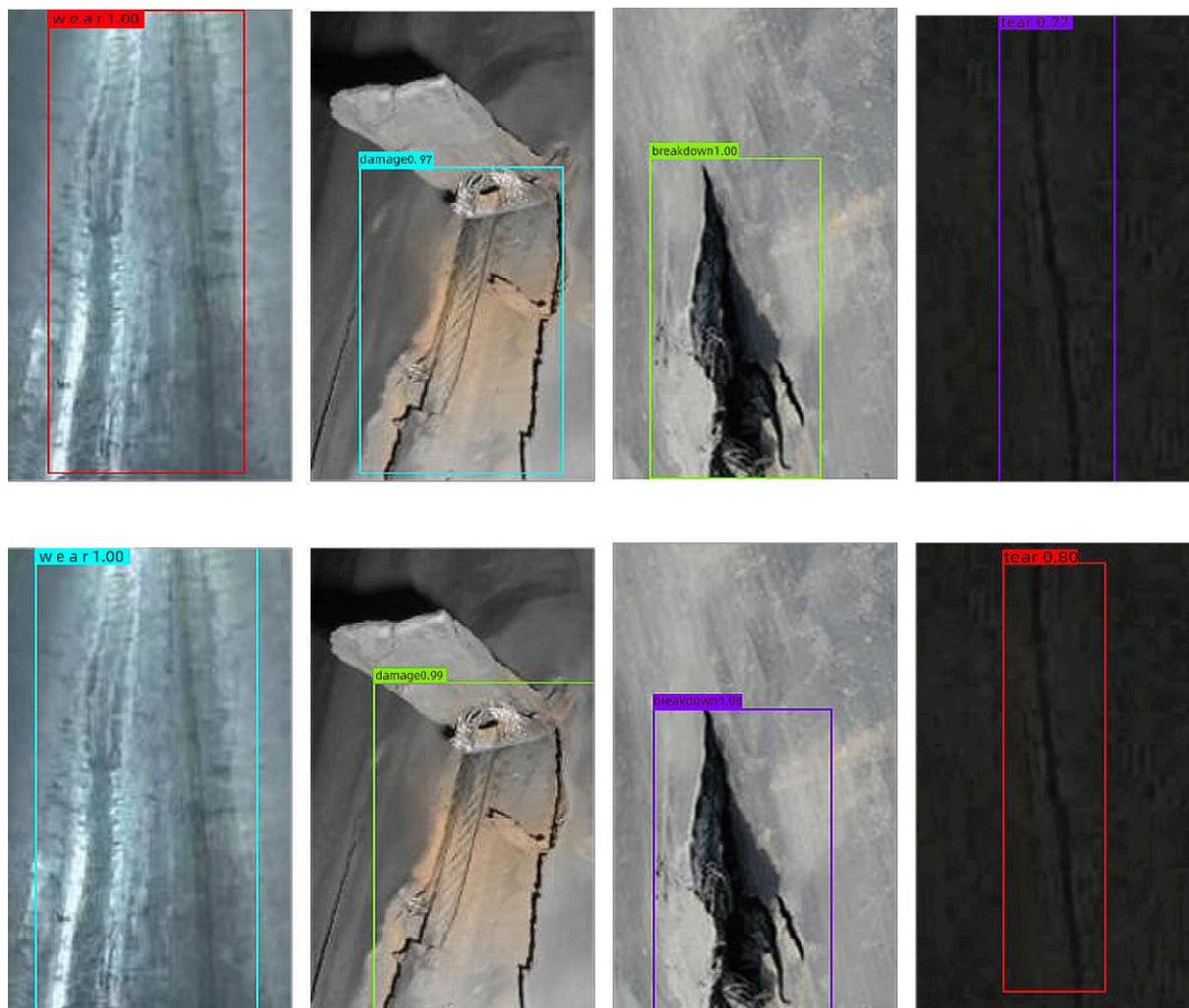


Fig. 6. The test results comparison between improved-Yolov3 and the original-Yolov3: Image (a)–(d) belongs to the result of original Yolov3, (e)–(h) belongs to the improved-Yolov3.

3.2. Hardware Usage Comparison of Multiple Algorithms

We also compared the hardware usage of different algorithms, including CPU, GPU(cuda), and RAM usage. Fig. 5 shows the comparison results, which guide field staff in selecting suitable algorithms. Better hardware resources increase detection speed, not accuracy.

Fig. 5 indicates that Improved-Yolov3 (with EfficientNet-B0) uses less GPU and RAM than the original Yolov3, with similar CPU usage. Faster R-CNN consumes more GPU and CPU due to its high FLOPS. As models expand, Improved-Yolov3 will consume more GPU and CPU, potentially surpassing Faster R-CNN. The proposed Improved-Yolov3 algorithm offers better timeliness while maintaining accuracy.

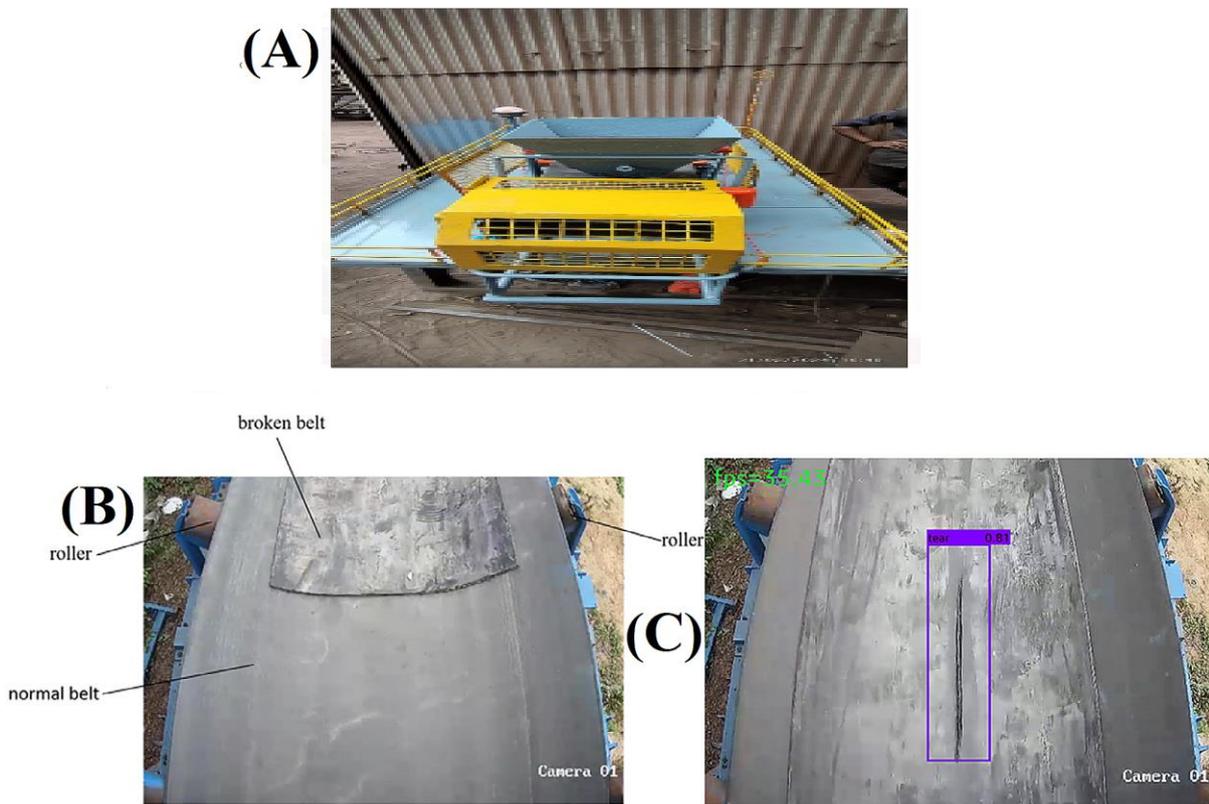


Fig. 7. Experimental setup.

3.3. Performance Comparison Between Yolov3 and Improved-Yolov3

Fig. 6 compares the performance of Improved-Yolov3 and the original Yolov3 on the dataset. Both algorithms effectively detect various conveyor belt damage defects. Unlike traditional image processing methods, deep learning-based detection allows direct localization and classification. The position and category probability of detected objects are shown in rectangular frames. Improved-Yolov3 shows higher accuracy, especially in tear detection, consistent with Table 1 results.

3.4. Verification of Model Generalization Ability

Generalization describes a model's ability to handle new data. After training, a model should accurately predict new data. To verify our model's generalization, we conducted field tests at Libo Heavy Industry Technology Co., Ltd. We pasted a damaged belt on a running conveyor belt as a test material (Fig. 7). The camera, installed above the transmission roller, had a frame rate of 25 fps and maximum resolution of 700×480 . The conveyor belt was 1.6 m wide, operating at 2.5 m/s. In practice, the camera should be placed on the lower return section, considering light and surface residues.

Fig. 7(d) shows the algorithm accurately identifying conveyor belt tears with 81% accuracy and 35.43 FPS, meeting project needs.

4. Conclusions and Future Work

Intelligent energization of belt conveyors is crucial for constructing smart mines. As the main component of belt conveyors, conveyor belt reliability impacts safe and efficient operation. Compared to traditional methods, our proposed deep-learning detection method offers significant improvements:

(1) We created a conveyor belt damage dataset with a redefined classification, including four damage types: surface wear, surface damage, breakdown, and tear. This detailed classification allows more accurate monitoring.

(2) We designed a deep learning-based conveyor belt damage detection method. The detection process is direct, requiring no auxiliary equipment or complex image processing. It detects four damage states and provides confidence levels.

(3) We improved the Yolov3 algorithm, balancing network width, depth, and image resolution during model scaling to enhance prediction accuracy.

(4) We considered hardware usage during algorithm operation to help engineers select appropriate algorithms.

Our improved algorithm doubles detection accuracy and speed, achieving up to 97% accuracy and 42 FPS. The proposed model also demonstrates high generalization ability on our test platform.

Future work will focus on model lightweighting to meet edge computing needs. We will also expand the conveyor belt damage dataset to enhance the neural network's robustness and generalization.

References

- [1] Y. Guan, J. Zhang, Y. Shang, et al., Embedded sensor of forecast conveyer belt breaks, in: International Conference on Fuzzy Systems and Knowledge Discovery, IEEE Computer Society, 2008, <https://doi.org/10.1109/FSKD.2008.643>.
- [2] H.I. Bozma, H. Yalçın, Visual processing and classification of items on a moving conveyor: a selective perception approach, *Robot. Comput.-Integr. Manuf.* 18 (2) (2002) 125–133, [https://doi.org/10.1016/S0736-5845\(01\)00035-7](https://doi.org/10.1016/S0736-5845(01)00035-7).
- [3] Z. Aichun, H. Gang, W. Yongxing, The research on the detection method of belt deviation by video in coal mine, in: 2011 International Conference on Mechatronic Science, Electric Engineering and Computer (MEC), IEEE, 2011, pp. 430–433, <https://doi.org/10.1109/MEC.2011.6025493>.
- [4] L. Xianguo, S. Lifang, M. Zixu, et al., Laser-based on-line machine vision detection for longitudinal rip of conveyor belt, *Optik* 168 (2018) 360–369, <https://doi.org/10.1016/j.ijleo.2018.04.053>.
- [5] Y. Pang, G. Lodewijks, Simulation-based knowledge acquisition for intelligent belt conveyor monitoring, Part. Part. Syst. Charact. 24 (4–5) (2007) 360–364, <https://doi.org/10.1002/ppsc.200601117>.
- [6] L.I. Zhanli, C. Jiaying, L.I. Hongan, et al., Research on intelligent monitoring and warning method of belt conveyor, *J. Graph.* (2017).
- [7] T. Andersson, M.J. Thurley, J.E. Carlson, A machine vision system for estimation of size distributions by weight of limestone particles, *Min. Eng.* 25 (1) (2012) 38–46, <https://doi.org/10.1016/j.mineng.2011.10.001>.
- [8] V. Redko, V. Khandetsky, P. Novak, et al., Method and apparatus for eddy current-based quality inspection of dry electrode structure: U.S. Patent 7355395[P]. 2008-4-8.
- [9] C. Hou, T. Qiao, H. Zhang, et al., Multispectral visual detection method for conveyor belt longitudinal tear, *Measurement* 143 (2019) 246–257, <https://doi.org/10.1016/j.measurement.2019.05.010>.
- [10] Michał Kontny, Machine vision methods for estimation of size distribution of aggregate transported on conveyor belts, *Vibroeng. Proc.* (2017) <https://doi.org/10.21595/vp.2017.19151>.
- [11] M. Kistner, G.T. Jemwa, C. Aldrich, Monitoring of mineral processing systems by using textural image analysis, *Min. Eng.* 52 (2013) 169–177, <https://doi.org/10.1016/j.mineng.2013.05.022>.
- [12] M. Yang, W. Zhou, T. Song, Audio-based fault diagnosis for belt conveyor rollers, *Neurocomputing* (2020) 397, <https://doi.org/10.1016/j.neucom.2019.09.109>.
- [13] Y. Pang, G. Lodewijks, A novel embedded conductive detection system for intelligent conveyor belt monitoring, in: 2006 IEEE International Conference on Service Operations and Logistics, and Informatics, Shanghai, 2006, pp. 803–808, <https://doi.org/10.1109/SOLI.2006.328958>.

- [14] K. Nienhaus, M. Warcholik, Christoph Büschgens, Belt positioning and skewing prevention in lignite mining using long-wavelength infrared cameras, in: Proceedings of the 12th International Symposium Continuous Surface Mining - Aachen 2014, Springer International Publishing, 2015.
- [15] S.G. Sakharwade, S. Nagpal, Analysis of transient belt stretch for horizontal and inclined belt conveyor system, *Int. J. Math. Eng. Manage. Sci.* 4 (5) (2019) 1169–1179, <https://doi.org/10.33889/IJMEMS.2019.4.5-092>.
- [16] Jayson Tessier, Carl Duchesne, Gianni Bartolacci, A machine vision approach to on-line estimation of run-of-mine ore composition on conveyor belts, *Min. Eng.* (2007) <https://doi.org/10.1016/j.mineng.2007.04.009>.
- [17] D. Dou, W. Wu, J. Yang, et al., Classification of coal and gangue under multiple surface conditions via machine vision and relief-SVM, *Powder Technol.* 356 (2019) 1024–1028, <https://doi.org/10.1016/j.powtec.2019.09.007>.
- [18] Z. Zhang, Y. Liu, Q. Hu, et al., Multi-information online detection of coal quality based on machine vision, *Powder Technol.* (2020) 374, <https://doi.org/10.1016/j.powtec.2020.07.040>.
- [19] Y. Gao, T. Qiao, H. Zhang, et al., A contactless measuring speed system of belt conveyor based on optical flow techniques, *IEEE Access PP (99)* (2019) 1, <https://doi.org/10.1109/ACCESS.2019.2937317>.
- [20] Y. Yang, C. Hou, T. Qiao, et al., Longitudinal tear early-warning method for conveyor belt based on infrared vision, *Measurement* 147 (2019) 106817, <https://doi.org/10.1016/j.measurement.2019.07.045>.
- [21] F. Klimenda, J. Soukup, J. Sterba, Noise and vibration analysis of conveyor belt, *Manuf. Technol.* 19 (4) (2019) 604–608, <https://doi.org/10.21062/ujep/341.2019/a/1213-2489/MT/19/4/604>.
- [22] M.H. Zhao, S. Ma, D.X. Zhao, Image processing based on gray information in sorting system of coal gangue, in: 2018 10th International Conference on Intelligent Human-Machine Systems and Cybernetics (IHMSC), 2018, <https://doi.org/10.1109/IHMSC.2018.10125>.
- [23] Y. Wang, Y. Wang, L. Dang, Video detection of foreign objects on the surface of belt conveyor underground coal mine based on improved SSD, *J. Amb. Intell. Hum. Comput.* (2020) <https://doi.org/10.1007/s12652-020-02495-w>.
- [24] M. Zhang, H. Shi, Y. Yu, M. Zhou, A computer vision based conveyor deviation detection system, *Appl. Sci.* 10 (2020) 2402, <https://doi.org/10.3390/app10072402>.
- [25] S. Kato, T. Nagayama, D. Su, et al., Identification of a cross-sectional vibration mode of a belt conveyor support structure using acoustic loading, *J. Struct. Eng. A* (2018) <https://doi.org/10.11532/structcivil.64A.354>.
- [26] Pytlik Andrzej, Klaudiusz, et al., Research on tightness loss of belt conveyor's idlers and its impact on the temperature increase of the bearing assemblies, *J. Sustain. Min.* (2016) <https://doi.org/10.1016/j.jsm.2016.07.001>.
- [27] Y.D. Zhao, M.F. Sun, Image processing and recognition system based on DaVinci technology for coal and gangue, *Appl. Mech. Mater.* 130134 (2012) 2107–2110, <https://doi.org/10.4028/www.scientific.net/AMM.130-134.2107>.
- [28] W. Liu, T. Qiao, G. Yan, et al., Research on visible light and infrared vision real-time detection system for conveyor belt longitudinal tear, *Iet ence Meas. Technol.* 10 (6) (2016) 577–584, <https://doi.org/10.1049/iet-smt.2015.0297>.
- [29] C. Aldrich, G.T. Jemwa, J.C. Van Dyk, et al., Online analysis of coal on a conveyor belt by use of machine vision and kernel methods, *Int. J. Coal Prep. Util.* 30 (6) (2010) 331–348, <https://doi.org/10.1080/19392699.2010.517486>.
- [30] R. Li, X. Yang, T. Liu, et al., Application of fiber optic sensors for vibration and ignition monitoring of a belt conveyor system, in: *Optical Fiber Sensors and Communication*, 2019.
- [31] S. Ren, K. He, R. Girshick, J. Sun, Faster R-CNN: Towards real-time object detection with region proposal networks, *IEEE Trans. Pattern Anal. Mach. Intell.* 39 (6) (2017) 1137–1149, <https://doi.org/10.1109/TPAMI.2016.2577031>.
- [32] Y. Yang, C. Miao, X. Li, et al., On-line conveyor belts inspection based on machine vision, *Optik* 125 (19) (2014) 5803–5807, <https://doi.org/10.1016/j.ijleo.2014.07.070>.
- [33] R. Yang, T. Qiao, Y. Pang, et al., Infrared spectrum analysis method for detection and early warning of longitudinal tear of mine conveyor belt, *Measurement* (2020) 107856, <https://doi.org/10.1016/j.measurement.2020.107856>.
- [34] B. Yu, T. Qiao, H. Zhang, et al., Dual band infrared detection method based on mid-infrared and long infrared vision for conveyor belts longitudinal tear, *Measurement* 120 (2018) 140–149, <https://doi.org/10.1016/j.measurement.2018.02.029>.

- [35] Grzegorz Peruń, Attempt to evaluate the technical condition of the rollers of the belt conveyor by vibration measurements, *Vibroeng. Proc.* 3 (2014) 296–299.
- [36] S. Kato, T. Nagayama, D. Su, et al., Identification of a cross-sectional vibration mode of a belt conveyor support structure using acoustic loading, *J. Struct. Eng. A* (2018) <https://doi.org/10.11532/structcivil.64A.354>.
- [37] F. Klimenda, J. Soukup, J. Sterba, Noise and vibration analysis of conveyor belt, *Manuf. Technol.* 19 (4) (2019) 604–608, <https://doi.org/10.21062/ujep/341.2019/a/1213-2489/MT/19/4/604>.
- [38] M. Zhang, H. Shi, Y. Yu, M. Zhou, A computer vision based conveyor deviation detection system, *Appl. Sci.* 10 (2020) 2402, <https://doi.org/10.3390/app10072402>.
- [39] Y. Gao, T. Qiao, H. Zhang, et al., A contactless measuring speed system of belt conveyor based on optical flow techniques, *IEEE Access PP* (99) (2019) 1, <https://doi.org/10.1109/ACCESS.2019.2937317>.
- [40] S.G. Sakharwade, S. Nagpal, Analysis of transient belt stretch for horizontal and inclined belt conveyor system, *Int. J. Math. Eng. Manage. Sci.* 4 (5) (2019) 1169–1179, <https://doi.org/10.33889/IJMEMS.2019.4.5-092>.
- [41] Y. Guan, J. Zhang, Y. Shang, et al., Embedded sensor of forecast conveyer belt breaks, in: *International Conference on Fuzzy Systems and Knowledge Discovery*, IEEE Computer Society, 2008, <https://doi.org/10.1109/FSKD.2008.643>.
- [42] Jayson Tessier, Carl Duchesne, Gianni Bartolacci, A machine vision approach to on-line estimation of run-of-mine ore composition on conveyor belts, *Min. Eng.* (2007) <https://doi.org/10.1016/j.mineng.2007.04.009>.
- [43] D. Dou, W. Wu, J. Yang, et al., Classification of coal and gangue under multiple surface conditions via machine vision and relief-SVM, *Powder Technol.* 356 (2019) 1024–1028, <https://doi.org/10.1016/j.powtec.2019.09.007>.
- [44] Z. Zhang, Y. Liu, Q. Hu, et al., Multi-information online detection of coal quality based on machine vision, *Powder Technol.* (2020) 374, <https://doi.org/10.1016/j.powtec.2020.07.040>.
- [45] Y. Gao, T. Qiao, H. Zhang, et al., A contactless measuring speed system of belt conveyor based on optical flow techniques, *IEEE Access PP* (99) (2019) 1, <https://doi.org/10.1109/ACCESS.2019.2937317>.
- [46] M. Yang, W. Zhou, T. Song, Audio-based fault diagnosis for belt conveyor rollers, *Neurocomputing* (2020) 397, <https://doi.org/10.1016/j.neucom.2019.09.109>.
- [47] Y. Pang, G. Lodewijks, A novel embedded conductive detection system for intelligent conveyor belt monitoring, in: *2006 IEEE International Conference on Service Operations and Logistics, and Informatics*, Shanghai, 2006, pp. 803–808, <https://doi.org/10.1109/SOLI.2006.328958>.
- [48] K. Nienhaus, M. Warcholik, Christoph Büschgens, Belt positioning and skewing prevention in lignite mining using long-wavelength infrared cameras, in: *Proceedings of the 12th International Symposium Continuous Surface Mining - Aachen 2014*, Springer International Publishing, 2015.
- [49] M. Kistner, G.T. Jemwa, C. Aldrich, Monitoring of mineral processing systems by using textural image analysis, *Min. Eng.* 52 (2013) 169–177, <https://doi.org/10.1016/j.mineng.2013.05.022>.