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ARTIFICIAL INTELLIGENCE (AI) TOOLS FOR THE REAL – TIME DETECTION OF TABLET DEFECTS

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ABSTRACT

Tablet defects such as capping, lamination, cracking, sticking, and coating irregularities can significantly compromise drug quality, therapeutic efficacy, and patient safety. Conventional inspection methods are largely manual, subjective, and labor-intensive, making them unsuitable for high-speed pharmaceutical production environments. Recent advancements in artificial intelligence (AI), particularly deep learning–based computer vision systems, have enabled automated and highly accurate real-time detection of tablet defects. This review examines the application of Convolutional Neural Networks (CNNs) and the You Only Look Once (YOLOv5) object detection algorithm for tablet defect identification and classification. CNNs facilitate automated feature extraction and defect classification from tablet images, while YOLOv5 enables rapid localization and multi-class detection within a single-stage framework. These AI-based systems significantly enhance detection accuracy, reduce human error, and support continuous monitoring in pharmaceutical manufacturing. Integration of AI-driven inspection systems within Quality by Design (QbD) and Process Analytical Technology (PAT) frameworks promotes improved process control, consistent product quality, and Industry 4.0–based intelligent manufacturing. This review summarizes principles, architecture, applications, advantages, and limitations of CNN and YOLOv5 models, highlighting their transformative role in modern pharmaceutical quality assurance.

KEYWORDS: Artificial Intelligence; Deep Learning; Convolutional Neural Networks; YOLOv5; Computer Vision; Pharmaceutical Manufacturing.

INTRODUCTION

Artificial intelligence (AI) has rapidly become a transformative force in pharmaceutical sciences, providing advanced solutions for drug discovery, formulation development, and quality control.[1,2] Machine learning (ML) and deep learning (DL) algorithms facilitate the analysis of extensive biological datasets, including genomics and proteomics, enabling target identification, prediction of drug–target interactions, and optimization of lead compounds. These methodologies contribute to shorter development timelines, reduced research costs, and enhanced success rates in drug approval processes.[3] Beyond drug discovery, AI increasingly supports pharmaceutical manufacturing and quality assurance. Tablets, as the most prevalent solid oral dosage form, are favored for their stability, accurate dosing, patient compliance, and cost-effectiveness.[4] However, manufacturing processes such as granulation, compression, drying, and coating may introduce defects including capping, lamination, sticking, picking, chipping, mottling, weight variation, and hardness variation. Even minor defects can negatively impact therapeutic efficacy, safety, and regulatory compliance. Traditionally, tablet defects have been identified through manual visual inspection or conventional optical systems, which are often subjective, labor-intensive, and susceptible to human error, especially in high-throughput production settings. These methods also suffer from inconsistent detection, limited sensitivity to subtle defects, inadequate traceability, and increased risk of product recalls.[5] Recent advancements in AI-driven machine vision systems have markedly enhanced defect detection accuracy and efficiency. AI-based inspection systems combine image processing, convolutional neural networks (CNNs), and pattern recognition techniques to automatically detect and classify surface and structural defects in real time. These systems are capable of inspecting thousands of tablets per minute, ensuring consistent quality while reducing labor costs and improving data traceability.[6,7] The integration of AI into tablet manufacturing aligns with Industry 4.0 principles by promoting automation, digital monitoring, and intelligent quality control. This review presents a concise overview of AI-based approaches for tablet defect detection, highlighting their advantages, limitations, and future prospects in pharmaceutical quality assurance.[8,9,10]

Tablet Defects

Tablet defects are deviations from the intended physical, mechanical, or aesthetic properties of compressed dosage forms that may compromise drug quality, performance, and patient acceptability.[8,9] These defects can originate from formulation variables, material properties, compression parameters, or environmental conditions during manufacturing.

Common tablet defects include

- Capping – partial or complete separation of the top or bottom of the tablet due to air entrapment or insufficient binding.[11]
- Lamination – separation of the tablet into multiple layers caused by over-compression, trapped air, or elastic recovery of granules.[12]
- Cracking – formation of fine fractures on the tablet surface due to mechanical stress or improper drying.[11]
- Sticking and picking – adhesion of granules to punch surfaces, often due to excess moisture, inadequate lubrication, or low melting components.[13]
- Chipping and edge erosion – breakage at tablet edges from weak mechanical strength or handling stress.[12]
- Mottling – unequal distribution of colour caused by improper mixing or dye migration.[10]
- Weight and content variability – inconsistent die filling or poor powder flow leading to non-uniform dosage.[11]
- Porosity variation and density heterogeneity – uneven compression resulting in non-uniform internal structure and altered dissolution behavior.[14]
- Coating defects – peeling, blistering, cracking, or rough surfaces due to improper coating formulation or processing conditions.[13]
- These defects may affect tablet hardness, friability, dissolution rate, bioavailability, and stability, thereby influencing therapeutic effectiveness and regulatory compliance.[12,14]

Conventional Methods for Detection of Tablet Defects and Their Limitations

Traditional tablet inspection relies primarily on manual examination and routine physical testing performed during or after manufacturing.[11,13]

Conventional Detection Methods

- Visual inspection for surface imperfections such as cracks, capping, colour variation, and coating defects.[13]
- Hardness testing to evaluate mechanical strength and compression quality.[11]
- Friability testing to assess resistance to abrasion during handling.[12]
- Weight variation testing to monitor dose uniformity.[11]
- Thickness and diameter measurement for dimensional consistency.[13]
- Disintegration and dissolution testing to assess performance characteristics.[12]
- Optical microscopy to examine surface morphology and minor structural irregularities.[14]

Limitations of Conventional Methods

Despite widespread use, these techniques present several constraints.

- Subjectivity and operator dependence in visual inspection reduce reproducibility.[13]
- Time-consuming and labour-intensive procedures, limiting suitability for real-time monitoring.[11]
- Inability to detect internal structural defects, such as density gradients or hidden voids.[14]
- Destructive testing requirements, preventing continuous process evaluation.[12]
- Limited sensitivity for early defect formation, leading to delayed quality control intervention.[13]
- Poor integration with automated manufacturing environments, restricting process optimization.[14]

Because of these limitations, conventional inspection methods are increasingly being supplemented or replaced by advanced imaging and artificial intelligence-based monitoring systems for improved quality assurance.[14]

AI TOOLS USED IN THE DETECTION OF TABLET DEFECTS

Artificial Intelligence (AI) has revolutionized pharmaceutical quality control by enabling rapid, accurate, and automated detection of tablet defects. Traditional inspection methods rely on manual visual examination, which is time-consuming, subjective, and prone to human error. In contrast, AI-based systems use advanced machine learning, deep learning, and non-destructive imaging techniques to identify both visible and hidden defects with high precision and consistency.

Modern AI tools such as deep learning models—including Convolutional Neural Networks (CNN), YOLOv5, and Autoencoders—analyse tablet images to detect surface defects like cracks, chipping, and discoloration. In addition, advanced imaging technologies such as X-ray microcomputed tomography, timeresolved microtomography, photoacoustic imaging, acoustic microscopy, and infrared diffuse reflectance spectroscopy enable internal and subsurface defect detection without damaging the tablet. Together, these AI-driven tools improve inspection speed, reduce human error, enhance product quality, and support real-time pharmaceutical manufacturing and regulatory compliance. The integration of AI into tablet defect detection represents a major step toward automated, data-driven, and high-precision quality assurance in modern pharmaceutical production. This study specifically explores the application of two advanced AI techniques—YOLO and Convolutional Neural Networks (CNN)—for precise and automated tablet defect detection.[15,16,17,18]

YOLOv5 (You Only Look Once – Version 5) for Pharmaceutical Tablet Defect Detection

Automated visual inspection has become an essential component of modern pharmaceutical manufacturing to ensure product quality, patient safety, and regulatory compliance. Deep learning–based computer vision models are increasingly being adopted for real-time quality monitoring in high-speed production environments. YOLOv5 (You Only Look Once version 5), developed by Ultralytics, is a state-of-the-art object detection model designed for fast and accurate real-time visual analysis. Built on the PyTorch deep learning framework, YOLOv5 enables simultaneous object localization and classification within a single processing step, making it highly suitable for industrial inspection tasks.[19,20,21]

Figure 1: Logo of YOLOv5 (You Only Look Once version 5).

In pharmaceutical tablet manufacturing, YOLOv5 enhances quality assurance by enabling automated, realtime detection of visually observable defects. This supports Good Manufacturing Practice (GMP) compliance by preventing defective products from entering the market, thereby improving product consistency and patient safety.[25,27]

Model Variants and Performance

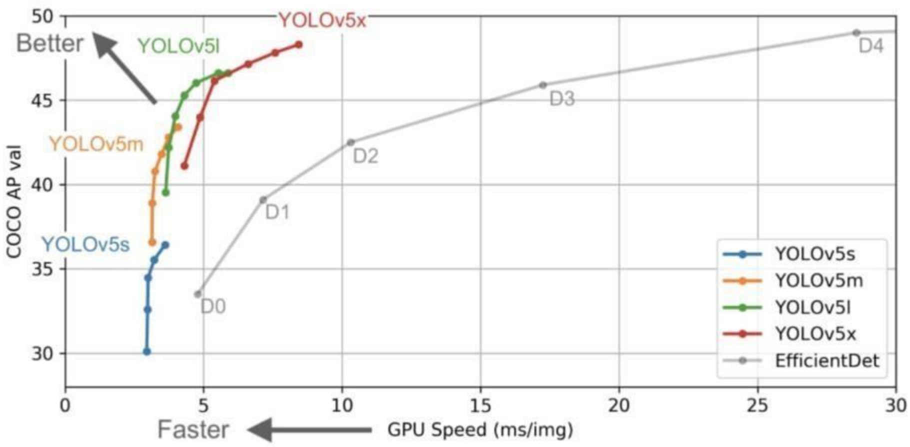

Figure 2: Different versions of YOLOv5.

Among the four versions – s, m, l, and x, YOLOv5s is fastest with low hardware needs, while YOLOv5x provides highest accuracy but requires powerful systems.[29] YOLOv5 is available in multiple model sizes, including YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x, designed to balance computational requirements and detection accuracy. Smaller models such as YOLOv5s provide high processing speed and low hardware demand, whereas larger models such as YOLOv5x offer superior detection accuracy but require more powerful computing resources.[19,22] This scalability makes YOLOv5 adaptable to different industrial inspection environments.

Principle of Object Detection

YOLOv5 is a single-stage object detection algorithm that identifies objects and predicts their spatial location simultaneously within an image. Unlike traditional multi-stage detection methods, YOLO-based models perform detection in one forward pass, resulting in significantly reduced processing time and enabling real-time inspection.[23] As a vision-based detection system, YOLOv5 primarily identifies externally visible defects in pharmaceutical tablets by analyzing surface appearance, geometry, and texture features.

Types of Tablet Defects Detected

YOLOv5 can detect a wide range of visually observable tablet defects, including:

1. Mechanical defects: cracking, chipping, capping, lamination, and fractured tablets.
2. Surface defects: spots, pits, scratches, contamination, and surface roughness.
3. Coating defects: peeling, flaking, colour variation, uneven coating, and mottling.
4. Shape and size defects: deformation, thickness variation, asymmetry, and dimensional irregularities.
5. Imprint defects: missing embossing, unclear markings, and double impressions.

Defects Not Detectable by YOLOv5

Because YOLOv5 is based on optical image analysis, it cannot detect non-visible or internal defects such as weight variation, content non-uniformity, dissolution abnormalities, hardness differences (without visible damage), or active ingredient inconsistencies. Its functionality is therefore limited to surface-visible quality attributes.

Architecture of YOLOv5

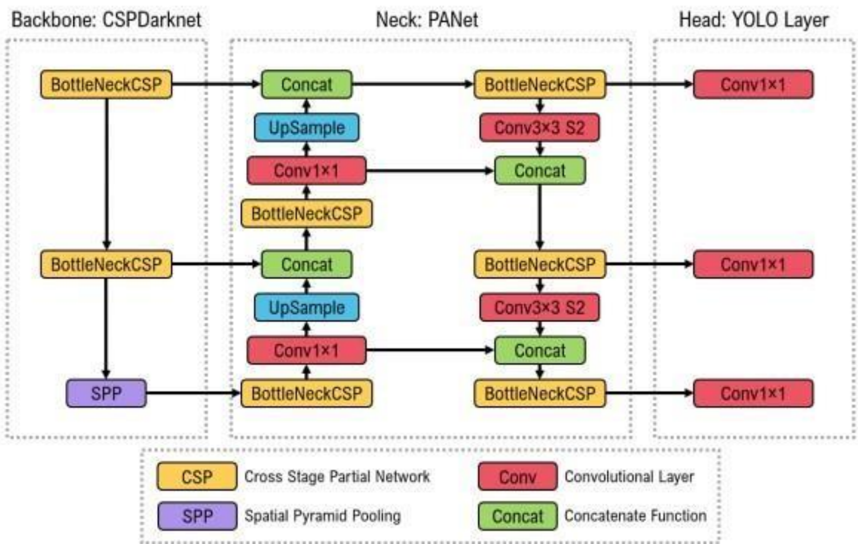

Figure: 3 Architecture of the YOLOv5 model, (i) Backbone: CSPDarknet, (ii) Neck: PANet, and (iii) Head: YOLO Layer.[30]

The YOLOv5 architecture consists of three primary components.

- Backbone – CSPDarknet: Extracts hierarchical features from input images.
- Neck – PANet: Aggregates multi-scale features to improve detection across different object sizes.
- Head – Detection Layer: Predicts bounding boxes, class labels, and confidence scores.

  Feature extraction is first performed by the backbone network, followed by feature fusion in the neck, and finally object detection output in the head layer,[19,24]

Working Principle in Tablet Inspection

In pharmaceutical tablet inspection systems, images of tablets moving on conveyor belts are captured using high-resolution cameras. The backbone network extracts relevant visual features such as shape, surface texture, and coating patterns. The neck component integrates multi-scale information, enabling detection of both small defects (e.g., pinholes or micro-chipping) and larger defects (e.g., cracks or fractures). The detection head then predicts bounding boxes and classifies defect types in real time.[25] This automated detection process reduces human inspection errors, enables continuous monitoring, and supports consistent quality assurance in high-throughput manufacturing environments.

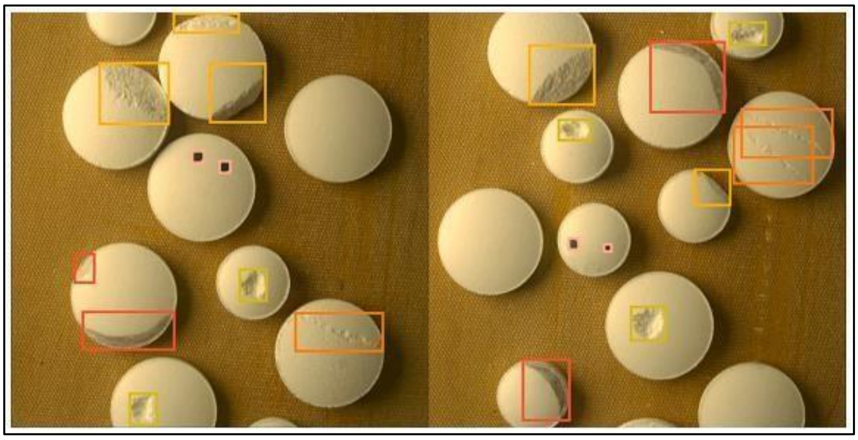

Figure: 4 YOLOv5 performs object detection.

Advantages in Pharmaceutical Tablet Defect Detection

YOLOv5 offers several advantages for industrial tablet inspection:

- Real-time detection suitable for high-speed production lines.
- Single-stage detection enabling simultaneous localization and classification.
- Multi-scale feature extraction allowing detection of both major and minor defects.
- Robust performance under variations in tablet colour, shape, lighting, and imaging conditions.[24,26]
- Capability to detect multiple defect types within a single unified model.
- End-to-end learning without handcrafted feature engineering.[23]

Applications in Pharmaceutical Manufacturing

YOLOv5 is widely applied in automated inspection systems for monitoring tablet compression, coating processes, and post-production handling. It enables early identification of compression defects such as lamination and capping, as well as coating irregularities including mottling and non-uniform film distribution. The model is also used for monitoring embossing quality and punch performance, supporting predictive maintenance strategies. In addition to real-time inspection, detection outputs can be used for batch-level defect monitoring and process optimization, contributing to continuous quality improvement.[27]

Limitations

- Detection performance depends heavily on the availability of high-quality labelled training data.[31]
- Limited capability for detecting internal or subsurface defects.
- Reduced accuracy when detecting extremely subtle defects with low visual contrast or under poor imaging conditions. Industrial Adoption.

Advanced AI-based vision inspection systems are increasingly used in pharmaceutical manufacturing. Major pharmaceutical companies such as Pfizer, Novartis, and Roche employ automated inspection technologies supplied by vendors including Cognex, SEA Vision, Antares Vision, and Omron. These systems incorporate deep learning models such as YOLOv5 to detect surface defects, coating irregularities, dimensional deviations, and packaging errors, thereby improving quality control and ensuring regulatory compliance.[32,33]

Convolutional Neural Networks (CNNs) in Tablet Defect Detection

Figure: 5 Logo of AT&T Bell laboratories.

Convolutional Neural Networks (CNNs) are deep learning models widely applied in automated visual inspection for pharmaceutical quality control. The modern CNN framework originated from the LeNet architecture developed by Yann LeCun at AT&T Bell Laboratories, which demonstrated automated feature extraction from images using back propagation.[34] CNN technology later achieved large-scale industrial relevance through Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton at the University of Toronto, where deep architectures combined with GPU computing significantly improved image recognition performance.[35] CNN models are currently implemented using deep learning frameworks such as TensorFlow and PyTorch, enabling automated, high-accuracy defect detection in pharmaceutical manufacturing environments.[36]

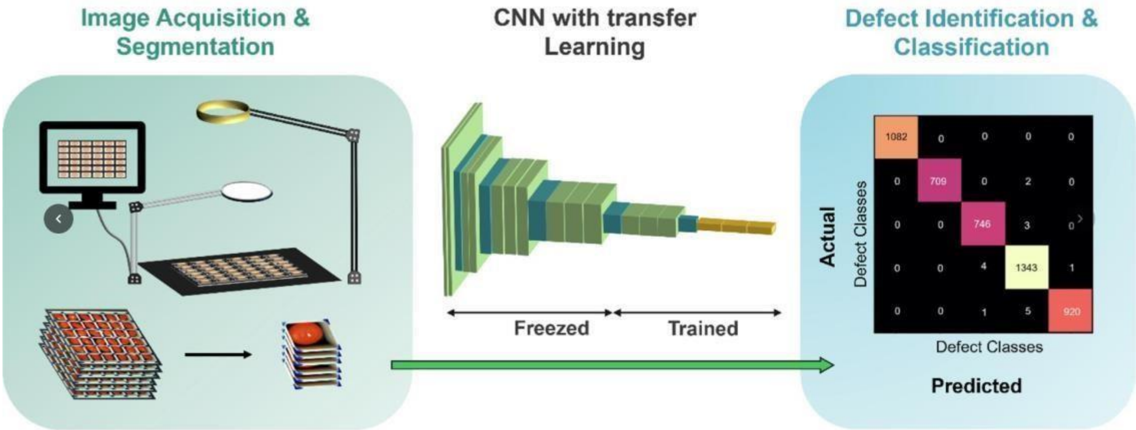

Figure 6: Workflow of CNN-based tablet defect detection system illustrating image acquisition, feature extraction using transfer learning, and defect classification.[40]

A CNN consists of multiple hierarchical layers that process image data for classification tasks. The architecture typically includes an input layer, convolution layers for feature extraction, activation functions for non-linear learning, pooling layers for dimensional reduction, fully connected layers for classification, and an output layer for prediction.[37] In tablet inspection, images captured by industrial cameras are pre-processed and analysed by convolution layers to detect visual patterns such as edges, cracks, texture variations, and colour irregularities. Extracted features are integrated through fully connected layers, and the final output classifies tablets as defective or acceptable.[38]

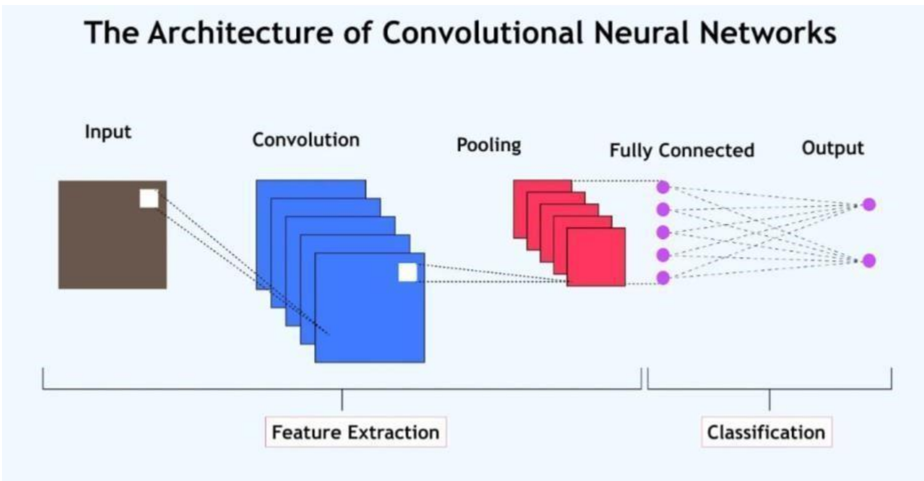

Figure 7: illustration of Convolutional Neural Network (CNN) used for tablet defect detection.

Defects Detectable by CNN

CNN-based inspection systems are highly effective in detecting surface-visible defects, including:

1. Physical defects
- Colour variation and mottling
- Surface contamination and black spots
- Scratches, abrasions, and warping
- Shape deformation and coating irregularities
2. Mechanical defects
- Cracking and fractures
- Chipping and edge breakage
- Compression-related surface damage.[38,39]

However, CNN models based on optical imaging have limited capability in detecting subsurface or nonvisual defects such as internal cracks, layer delamination, coating thickness variation, density heterogeneity, and formulation-related abnormalities.[39]

Applications

CNNs are widely used for automated surface inspection of tablets during compression and coating processes. They support real-time in-line monitoring, defect localization, and automatic rejection of defective units. These systems also enable multi-defect classification and batch-level quality trend analysis, improving process control and manufacturing efficiency.[38]

Advantages

- Automatic feature extraction without manual intervention
- High detection accuracy for diverse visual defects
- Robust performance under variations in lighting, colour, and imaging conditions
- Capability for multi-class defect classification
- Integration with automated inspection and quality control systems.[37,38]

Limitations

- Requires large labelled datasets for reliable model training
- Limited detection of internal or non-visual defects
- Performance variability across different imaging environments (domain shift)
- Need for periodic retraining to maintain industrial accuracy.[39]

CONCLUSION

Artificial intelligence has transformed tablet defect detection from manual, subjective inspection to automated, high-precision real-time monitoring. YOLOv5 provides rapid object detection suitable for industrial environments, while CNNs offer high-accuracy classification of surface defects. Although challenges remain in detecting internal defects and ensuring dataset generalization, AI integration into pharmaceutical manufacturing aligns strongly with Industry 4.0 principles and PAT frameworks. Future advancements combining AI with advanced imaging modalities such as micro-CT and hyperspectral imaging may further enhance internal defect detection capabilities. AI-driven quality control represents a critical step toward intelligent, data-driven, and fully automated pharmaceutical production systems.

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