Using AI image recognition to find flaws in syringes during the manufacturing process

The automated production of goods has become much more common with recent advancements in technology. The total spending for the construction of manufacturing facilities has nearly doubled in the U.S. since 2022, with around 100 billion more dollars spent in 2023 (Nostrand et al., 2023) The increase in spending would allow for the construction of more factories, processing plants, and mills, which would increase manufacturing efficiency. These facilities increase efficiency through various means such as optimized workflows, assembly lines, and automation. In particular, automation allows for much faster production of goods and services and is a large factor in mass production.

Computer error, however, can prevent automated manufacturing from being completely human-independent. Machines can incorrectly fabricate components due to poor materials or equipment failure, for example (Mörke, 2024). Minor mistakes made during the creation of a physical object could cause permanent changes to its structure, potentially inhibiting its ability to function properly. These mistakes during automation are known as manufacturing defects, and companies are developing solutions to prevent these defective products from leaving the factory, as they could decrease consumer satisfaction and brand reputation. Currently, humans are commonly tasked with detecting defects in freshly made products. However, laborers can easily miss defects, considering that they can experience fatigue while slowly scanning dozens of objects for various types of defects (Paul et al., 2023). On top of this, labor can be extremely time-consuming and costly for companies, necessitating a detection method that is faster, cheaper, and more accurate. Neural networks are gaining popularity as an approach to this problem, as they have shown promise in other classification tasks such as big data processing (Ramachandran, 2024). Convolutional neural networks (CNN) can be specifically trained to recognize patterns in images. In this case, various filters are applied to an image so that the neural network can understand the image it is analyzing. Afterward, the model can make predictions on the location of objects of interest in the overall image (Ferguson et al., 2018).

When it comes to automated manufacturing, CNNs can be used to analyze each object on the production line by taking a picture of an item and identifying defects through the image, helping determine if that item meets quality standards. With high amounts of training, CNNs can reach levels of speed and accuracy that exceed that of a human (Kaur, 2024), negating the need for slow and methodical checking, and encouraging the implementation of a real-time and instantaneous defect detection system that can identify not only defects but also their locations and type. In fact, CNNs have been successfully used before for finding defects in manufacturing, such as for finding flaws in screws (Kuo, 2020).

Image recognition models are not flawless, however. For example, to train an image recognition model, hundreds of images must be gathered of a single product, and in the case of defect detection, images of both undamaged and damaged versions of the product must be captured so that the neural network can learn to differentiate between the two. Capturing images can be difficult if many images of a defective product do not exist in the first place. Environmental conditions are also important during scanning while manufacturing, as a slight difference in lighting or background from training data can cause the model to make incorrect predictions on where defects are located from the images it takes. Compromises must also be made between speed and accuracy, as real-time defect detection will need extremely high levels of speed, which may limit accuracy (Ferguson et al., 2018). However, even though image recognition models may have limitations that prevent them from being perfect, they are still far more efficient than humans at defect checking and a viable option as long as the time and effort can be spent in training and establishing a CNN.

In the medical industry, products should be scanned for defects before they are shipped out to hospitals. An important example of this is syringes. Syringes are a very commonly used medical instrument that can inject and withdraw liquids from the human body. Over 16 billion injections are administered yearly, providing medical assistance to hundreds of thousands of people worldwide (Moustafa et al., 2021). The manufacturing process of syringes involves the use of multiple automated machines and mills, like various other medical devices. However, mistakes can be made during manufacturing due to machine error. In the UK, for example, aseptic syringe products alone have been found to have a defect rate of 0.49% (Bateman, 2010) which can mean thousands of syringes with defects at the larger scale. Below is a more detailed table that describes the various aseptic syringe products and where errors were found during manufacturing over 3 years in the UK.

	Stage at which error detected									
Product type	First check in assembly area	Operator check in preparation area	During labelling	Final check prior to release	At release stage	In clinical area prior to administration	In clinical area during or after administration	Other	Not recorded	Total
Cytotoxic adult	1045 (55.9%)	109 (5.8%)	47 (2.5%)	451 (24.1%)	65 (3.5%)	108 (5.8%)	7 (0.4%)	31 (1.7%)	5 (0.3%)	1868
Cytotoxic paediatric	27 (24.3%)	11 (9.9%)	5 (4.5%)	41 (36.9%)	6 (5.4%)	16 (14.4%)	1 (0.9%)	4 (3.6%)	0	111
Parenteral nutrition—adult	383 (56.2%)	56 (8.2%)	30 (4.4%)	99 (14.5%)	43 (6.3%)	22 (3.2%)	4 (0.6%)	43 (6.3%)	1 (0.1%)	681
Parenteral nutrition—paediatric	74 (41.3%)	21 (11.7%)	0	47 (26.3%)	16 (8.9%)	7 (3.9%)	3 (1.7%)	11 (6.1%)	0	179
Other intravenous additive	504 (39.3%)	179 (14.0%)	128 (10.0%)	262 (20.5%)	110 (8.6%)	35 (2.7%)	6 (0.5%)	56 (4.4%)	1 (0.1%)	1281
Other prefilled syringes	60 (19.4%)	24 (7.7%)	4 (1.3%)	76 (24.5%)	78 (25.2%)	9 (2.9%)	1 (0.3%)	58 (18.7%)	0	310
Other	68 (31.3%)	33 (15.2%)	7 (3.2%)	35 (16.1%)	40 (18.4%)	3 (1.4%)	2 (0.9%)	26 (12%)	3 (1.4%)	217
Not recorded	24 (54.5%)	3 (6.8%)	3 (6.8%)	8 (18.2%)	2 (4.5%)	2 (4.5%)	0	0	2 (4.5%)	44
Total	2185 (46.6%)	436 (9.3%)	224 (4.8%)	1019 (21.7%)	360 (7.7%)	202 (4.3%)	24 (0.5%)	229 (4.9%)	12 (0.3%)	4691

Figure 1: Syringes with errors detected during manufacturing in the UK (Bateman, 2010)

With 958,532 aseptic syringes made in the UK during the period, 4,691 of them contained defects. This is especially concerning because improper syringe function in a medical scenario could potentially cause severe harm to a patient. Therefore, a CNN can be employed to determine if any defects are present in newly manufactured syringes, preventing dysfunctional syringes from ever reaching hospitals.

The project proposes a CNN model that can detect defects in syringes during the manufacturing process in real time. The rest of the paper will discuss the specific aims that will need to be addressed for a strong model to be developed, the methodology for creating that model, and preliminary data to ensure the model meets the specific aims.