The Application of Deep Learning in Quality Assurance for U.S. Manufacturing

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1. Introduction to Deep Learning and Quality Assurance

Quality of products has always been a major concern for companies, and the advent of deep learning is adding more value and efficiency to quality assurance as it does in many other applications. Specifically, in the U.S., manufacturing has always had stringent quality assurance guidelines and has previously been aided by other forms of machine learning. The scope of this essay is to present how deep learning has been applied to complex, large-scale quality assurance systems to better inform U.S. producers' potential for employing these new technologies. In the following section, the necessary background for this new development is laid out: a primer into deep learning and its practical application, as well as an overview of why quality assurance is and will continue to be vital for U.S. manufacturing.

Deep learning is quickly becoming one of the most talked-about subsets of machine learning due to its ability to learn representations of data through the use of neural networks. There are no good definitions that completely capture the complexities of deep learning, except to say that it can refer to any number of network structures that seek to emulate the human brain, learning and expressing data through the use of multiple nonlinear transformations. In this regard, deep learning has been particularly useful in image and speech recognition, natural language processing, and drug discovery. Generally, the more data through which deep learning can train, the better the output.

1.1. Overview of Deep Learning

Deep learning is a class of machine learning algorithms that uses multiple layers to progressively extract higher level features from the raw input. These higher level features can be used for classification, clustering or regression. The performance of deep learning methods has been improving as more labeled data and computational resources become available.

Some common deep learning models that have been applied are neural networks and their extensions, including convolutional neural networks (computer vision), recurrent neural networks, and autoencoders. Convolutional neural networks are ideal techniques used for feature extraction from large datasets. Meanwhile, recurrent neural networks are used for dynamic modeling of sequential patterns in RAM data.

This study is interested in studying the use of deep learning algorithms, with a focus on the popular recurrent neural network, as quality assurance tools. However, it is important to understand the concept and workings of the underlying algorithms. We will continue this section by discussing neural networks as the foundational technology of deep learning. Neural networks are used to solve different kinds of tasks, such as unsupervised learning, supervised learning, semi-supervised learning, and reinforcement learning. The network is a layered architecture of nodes, each connected to the adjacent layer. The nodes themselves do not perform any interesting computation; for example, sigmoid is a common activation function used to perform computation.

1.2. Importance of Quality Assurance in Manufacturing

Quality assurance (QA) is fundamentally about managing risk and improving outcomes. In manufacturing, it builds customer trust and satisfaction, which encourages business growth. For products and processes, higher reliability levels and lower variability, as a result of improved quality, enable firms to increase turnaround speed and, with confidence, make longer-term decisions regarding capital investments.

The healing factor cannot be denied as a major coup of using deep learning in manufacturing. Deep learning's ability to autonomously and fully recover from the numerous correctable mistakes that it makes on the job is a significant advantage. For standard machine vision quality analytics, additional assumptions must be made and testing must be performed (especially those tied to computer vision approaches) to reach an equivalent endpoint. Only being able to predict finished product quality, especially on welding projects, is another method in which deep learning may be beneficial. This system needs some resistance spot welds to be punched on a vehicle body panel, skipped after accurate assessment, and the vehicle to move on in the production pipeline.

2. Fundamentals of Deep Learning

The core of artificial intelligence is, without any doubt, deep learning. This is both because it utilizes neural networks to enable basing hierarchical concepts, but also because hidden layers enable information to become more abstract. Deep learning uses various layers of such computational resources, and hidden layers are the parts in-between the input and output layers that provide more abstract information. Formulating these connections is also the subject of the machine learning aspect of deep learning. Neural networks are composed of nodes and connections to the brain, and several layers form a deep learning network for the input nodes. Neural networks that are very deep, in contrast, need this level of analysis to make sense of complex data like natural language or scenes because they have the same fundamental aspects but to a much more defined extent.

In areas like standard backward networks, convolutional neural networks have developers improve the connections between develop new structures that solve the new difficulties they face and develop new structures that conquer the new challenges they would confront by modifying these connections. One compelling example of this is developing convolutional neural networks to focus the most on the edges and corners because there is a sizeable meaningful relationship that they have to include with a tailored application like deep learning to improve it. Because of this, it is helpful to extract the subject of the paper not just from surface-level meaning (as in the earlier instance), but it is also valuable to extract representations over time. Experiments demonstrated that using both approaches led to better results. RNNs provide a methodological framework for using varying sequences, particularly for natural language processing or change illustrations, to perform recursive applications.

2.1. Neural Networks

Neural networks are one of the most studied deep learning algorithms. A neural network is a technology built on an artificial structure that functions similarly to the human brain in that it learns through experience. The neural networks have an assemblage of data - which is the input layer, a series of algorithms - which is the hidden layer, and the output layer, which is the result. Neural networks can be considered one type of clustering and segmentation group. In the offering of the internet, many different kinds of neural networks are used in different settings. They have been proven to immensely achieve outcomes from a simple restriction up to a very complex situation using multiple layers. Numerous algorithms are used in the analysis and recommendation of MOOC systems.

The neural network model receives fine, observational inputs of an individual and identifies a sequence of dimensions that learn higher representations and might be converted. They are powerful performers in the automatic discovery, investigation of the core end-features that are absorbed from the input features, and improve the performance of the tasks. In the applications of U.S. quality assurance manufacturing, these neural networks are nowadays applicable because with the size of data they can perform the actual phases of segmentation, classification, interpretations, decision systems, and representations. The manufacturing of companies like computer applications, electronic components, paper-based applications, and automobile datasets are continuously increasing in size.

2.2. Convolutional Neural Networks

The convolutional neural networks are a specialized kind of feed-forward neural networks. CNNs are considered standard for image and video applications and are now routinely used in numerous areas. They have the ability to take in an input volume and assign importance (learnable weights and biases) to various aspects/objects in an image and be able to differentiate one from another. Some of the important operations occurring within a convolutional neural network are convolutional layers, ReLU, pooling layers, and fully connected layers. Each of these operations is explained in more detail in the following sections.

One of the primary reasons for using CNNs in a quality assurance setting is in the foundational design to take 2D raw image input for classification. As such, they are linear and have multiple assets including robustness to image manipulation, automatic feature extraction, and translation invariance. For manufacturers, this is preferable since it could generalize well over time and not require retraining if engineered equipment changes. Furthermore, the capability of learning identified features causing a defect, even in environments laden with noise, is critical. Most fundamentally, the CNNs can assure that defects are systematically detected. Given rapidly evolving manufacturing technologies, the ability to normalize these technologies then run training could be advantageous, and CNNs are ideal for doing this. Overall, CNNs could be beneficial to the U.S. manufacturing industry, where the development of rapid, convenient, and low-cost measurement technologies remains a priority.

2.3. Recurrent Neural Networks

A recurrent neural network, commonly abbreviated as RNN, is a type of artificial neural network (ANN). The associated computational property enables its concurrent operation with respect to time-domain sequential data. This unique characteristic explains its typical utilization for deep learning temporal datasets: deep learning, in practice, considers recurrent neural networks as suitable choices to some extent. A possible common and repetitive application of RNN involves the processing of topics like speech content and text representation. The frame-to-frame semantic video content of spatial-temporal sequences—another function RNN commonly presents—makes it a main choice as part of some deep learning design tasks. Specifically, some of these tasks include image-to-speech and temporal datasets that use nonlinear recurrent solutions for designing spatiotemporal sequences. Thus, it is important to note that in the context of this paper, the recurrent neural network is a branch of deep learning that can enable many benefits for industrial users. This knowledge will be further substantiated in the following subsections.

Recurrent neural networks: modeling purposes. RNN is capable of expanding certain model customization applications, some of which include applications relevant to the U.S. manufacturing industry and are mentioned in this list. The first three modeling purposes correspond to video modeling, i.e., RNN can be implemented using video feature vectors and deploy predictive forward, predictive forward dual, and feature fusion loss network topologies.

3. Quality Assurance Techniques in Manufacturing

John L. William founded the William Institute program in 1986, focusing on quality maintenance for manufacturers. He was interested because of the competitiveness within the U.S. manufacturing sector. Currently, a number of techniques are in use to some extent to help manufacturers assure quality. These include: Statistical Process Control (SPC) using variables, SPC using attributes, SPC issue tracking, Six Sigma, The Malcolm Baldrige (MB) Award, The "Deming Prize" of Japan, The Shingo Prize for Excellence in Manufacturing in the U.S., Failure Mode and Effects Analysis (FMEA), Total Quality Management (TQM) and its variant ISO 9000. W. Edward Deming and others have worked with businesses to improve the quality of products through quality control (QC) and quality assurance (QA).

Statistical process control and quality assurance (SPC-QA) have been applied in various forms. The most popular approach typically used measurements made during production to provide real-time feedback to make decisions with regard to the production process. All rely in part on sampling to help ensure the quality of the product. Often special customer requirements influenced the choice of the technique to be implemented. Consequently, more and more techniques are used in various combinations for quality assurance. In addition, manufacturers are trying to expand the tools available in order to keep bad products out of the hands of the customer, in order to avoid costly recalls and damage to their reputation. Many companies also responded to incentives to use quality assurance methods after promising never to use fancy methods.

3.1. Statistical Process Control

Statistical process control (SPC) refers to the practice of constantly monitoring and managing processes to maintain quality standards. An industrial example of SPC is an automatic feedback control loop in a machine control system. Material flows through processes to be cut, drilled, folded or welded, etc. Signals from various sensors monitor the states of these machines (temperature, pressure, vibrations, wear, noise level in manufacturing, etc.) of the equipment. Control algorithms then adjust the machine parameters in order to maintain quality or adjust to specific unique characteristics without stopping production. Smoothing processes, such as signal processing or filtering, use statistics in the time or frequency domain to emphasize the key features of data. For example, a filter can smooth the power spectrum of a signal by removing noise and focusing on the fundamental components of the system.

On a wider scale, in Six Sigma, quality is captured utilizing a set of SPC-aided metrics, such as Defects per Million Opportunities (DPMO). In addition to tracking manufacturing defects and continuous monitoring of plant conditions, process capability analysis (when a process is in statistical control) can quickly identify problems and reveal hidden costs within processes. From fabrication to distribution, SPC is implemented in industries for several different processes, such as managing product texture of perishable consumables, controlling diesel fuel properties manufactured for U.S. navy bases, and other applications. In this work, the seventh and final domain of the Lean Six Sigma framework for SPC is used to monitor and manage process variability within the manufacturing subdomain: errors within designs and measurements are unavoidable. The variability of designs and measurements will be quantified with statistics to measure model uncertainty and to describe relationships. This work investigates the use of deep learning in both classification and regression problems for

SPC within U.S. manufacturing processes. Given the importance of quality management to the safety and health of the public, the focus of this study is shifted to all seven levels of a new framework in Lean Six Sigma for assessing longitudinal level of safety and health practices.

3.2. Six Sigma

In 1986, the Six Sigma method was coined and implemented by Bill Smith at Motorola for quality and productivity. In 1995, General Electric's CEO Jack Welch utilized Six Sigma to accomplish incredible product quality. There are various phrases and statistics about Six Sigma, such as 3.4 DPMO (defects per million opportunities), 99.9997% perfection, 1.5σ shift, and 99.99% accuracy. Motorola, General Electric, and Merck & Co. have saved between $800 million and $1 billion per year using Six Sigma. In the United States, many other companies and organizations have embraced and earned the Six Sigma tradition. A Six Sigma black belt is someone who has finished Six Sigma training and has proven that he or she is committed to the principles of excellence and client focus. In a nutshell, Six Sigma is a strategy for maintaining top quality and excellent consumer care, as well as producing goods and services for as little time and money as practicable. The purpose of Six Sigma is to produce as few faults or mistakes as necessary by direct client movement on the various processes or activities incorporated to purchase and order supplies from producers. It is a testable and repeatable definition that has a scientific foundation.

In manufacturing, U.S. customer standards are some of the most challenging. According to the U.S. Small Business Administration, 1% of small businesses export, and the worldwide market estimated population of consumers is 95% of these U.S. export-based companies. As a result, for commodity manufacturers to submit competing offshore items, they must reach the top value in accordance with U.S. consumer satisfaction. Companies in the United States must focus on and extend their cutting-edge values. A deep learning method to improve the effectiveness of Six Sigma is scheduled for U.S.-based suppliers, although few will concentrate on aggressive applications such as LSTMs in the context of manufacturing. This research is essential to U.S. manufacturers because deep learning approaches are being used in a wide variety of fields, but the results have not yet been researched. For U.S. companies, the rising of those outcomes has a high value.

3.3. Failure Mode and Effects Analysis (FMEA)

Failure Mode and Effects Analysis (FMEA) has emerged as an effective technique used by a variety of industries in the presence of new technologies, products, or processes. In the context of U.S. manufacturing, practitioners associated with mechanical and automotive parts, neurobiotics, and facilitating technologies have nominated it as a promising approach. The use of FMEA is to provide a systematic means of identifying and addressing potential failure modes. It is, therefore, an appropriate tool to begin an in-depth examination of the potential role of deep learning in quality assurance because it is the most dominant approach within these industries targeted for the analysis. A structured, systematic tool will allow for easier identification of critical characteristics and features relevant to both deep learning and quality. Furthermore, increased understanding in this area could lead to more effective applications of deep learning models in quality assurance.

FMEA is a structured technique used to define and characterize all potential failure modes of a process or a product. FMEA is based on a construction method that gives a view of the process or product while probing the models or techniques of deep learning and quality assurance discussed clarity on the objective of the investigation, the relevance of the characteristics under investigation. The highest levels of quality are often set by customers in agreement with manufacturers. The failure mode and effect analysis (FMEA) technique for monitoring systems is used. The occurrence ranks indicate that the technique is good for monitoring computer hardware or software that impacts the process of safety-critical applications. By analyzing and synthesizing analysis, the theory of the technique was developed. For secondary systems that have implications for the process, the highest occurrence rank was achieved. A thorough elucidation involves using a combined expert judgment risk index and Pearson correlation analysis indices, illustrated with numerical case studies.

4. Integration of Deep Learning in Manufacturing Quality Assurance

Quality assurance in a manufacturing environment involves multiple steps. These include data collection, data preprocessing, model training, model validation, and system implementation. The discussed approach integrates deep learning techniques into a quality assurance set-up. In our case, we are focusing on a deep learning technique for image classification, as this is one of the main ways that consumers will interact with our variable data line. Furthermore, the integration of object detection/bounding box system highlighted below will allow for localization of where and when any potential problems arose in a given process cycle. As we have recognized that our incoming and outgoing quality indicator and precision checking system play a significant role in our overall process, being able to track down where problem areas are occurring is a big plus and allows for more granular checks to be implemented.

Data collection is the first step in any deep learning task. This involves sourcing the images that will be used to train the overall quality assurance (model) system. We acquired images and built out our test data set and train data set for the TCs. These images were based on product movement at a controlled velocity. The TC images were sourced over a period of 15 days in 'real'-almost real time. In particular, thousands of images were captured for both normal and non-conforming product. Data processing included the resizing of output images, normalization, and the transformation from standard numerical arrays to a format that the deep learning framework, due to be used, could utilize. During and immediately after data collection, numerical data provided further insight into process key performance indicators that were looked at. Finally, we utilized a method for upsampling images in which little 'defect' is present, while marked up 'defect1', 'defect2', and 'defect3' images were downsampled. This dealt with a large level of class imbalance in the RGB images that our tests carried out.

4.1. Data Collection and Preprocessing

4.1.1. Data Collection in Quality Assurance for U.S. Manufacturing The collection of manufacturing data has always been a cornerstone in quality management, and as inspection processes become more automated, the potential for big data grows. Fortunately, many U.S. manufacturing firms are already engaging in the data collection and preprocessing process, capturing and storing the salient and necessary information for incorporating deep learning into quality assurance tasks such as predictive maintenance. This is often performed more out of cost-saving drive than an intentional move toward deep learning, though; a 2017 study by Capgemini found that, of 500 U.S. manufacturers surveyed, 10% were using predictive maintenance on a deep learning algorithm, but 76% were utilizing predictive maintenance in some capacity.

4.1.2. Preprocessing in Quality Assurance for U.S. Manufacturing Data preprocessing involves a variety of tasks, from making sure that the data collected is clean and consolidated in a single database to filling in any missing values, downsampling or otherwise transforming data to accommodate algorithmic needs, removing redundant parameters, and deciding the best way to label the data according to which supervised learning system is chosen. The preprocessing task tends to take the longest amount of time in deep learning applications, but it has become increasingly straightforward over the years and is doubtless performed to some extent by all U.S. manufacturing companies, especially those with data centers. While the authors are not aware of a study that specifically examines data preprocessing in the context of training deep learning models, recent studies examining K-means clustering and dimension reduction are evidence that data are manipulated in such a way as to accommodate deep learning systems.

4.2. Model Training and Validation

3.4.2. Model Training and Validation. Model training is a vital stage of integrating deep learning in manufacturing quality assurance, as it develops a model that will learn from the data. There are several popular machine learning toolkits to develop models. Commonly employed open source libraries include TensorFlow, Keras, PyTorch, and Theano. In the current work, TensorFlow was used to develop the deep learning models. TensorFlow, originally developed by researchers and engineers of the Google Brain Team, is an open source library for numerical computation developed by Google. The main component of TensorFlow is its data flow graph, comprehensive libraries, and tools that help researchers and developers create and deploy machine learning models both in research and industrial applications.

Model validation is a crucial stage to assess the quality of the model's generalization. It tests for different situations to find how the model behaves beyond the training/testing data used, to make sure the model does not overfit, where the model performs very well on the seen data (training/testing data) but poorly on unseen data. Overfitting usually occurs as the model learns both the pattern of the data and noises or errors. Several parameters dictate how a model is trained, including input data, network architecture, learning rate, activation functions, batch size, layers, size of each layer, etc. Tweak different parameters during the training to find the most optimal hyperparameters. Hyperparameter tuning can take a long time, and a grid search may be a daunting task.

5. Real-World Applications of Deep Learning in U.S. Manufacturing

In the real world, deep learning proves beneficial for a few key tasks in U.S. manufacturing. One major area of concentration is defect detection, which spans multiple industries. Asahi Glass and AerNos are developing AI-driven systems to detect defects in glass and gas sensors. In Volvo's Ghent, Belgium, manufacturing plant, AI is used to guide robots in guiding glue to the right point on windshields, while calibrating, cleaning, or replacing emission sensors before cars become inoperable. AI also uses laser displacement sensors facing inward to immediately detect unset glue. Finally, the system also performs 100% of the body-side glue bead inspection, flagging up any major defects for further operator attention. Steel manufacturers also have a desire to use AI for real-time post-defect analysis on their fabrication lines, as does Duerr, a major maintenance systems provider. Resource Equipment Limited, a manufacturer of oil and gas mining and transportation equipment, developed an AI system that can detect 90% of defects in welds. Bosch in Nashik, India, and Ashok Leyland, a commercial vehicle manufacturer in Chennai, India, use deep learning for defect classification.

Predictive maintenance is a form of quality assurance. Quantum uses AI for maintenance prediction and diagnostics. Steinmeyer, a German engineering company, uses AI to produce motors with predictive maintenance for machines in industry. Miba proposes the use of deep learning for the automated parameter tuning of an e-machine. Magnetic Insight uses the same technology (transfer learning) to build predictive maintenance plans for its small fleet of clinical imaging equipment. Magnetic Insight fills the role as a manufacturer because it machines tools its clinical instrument to less than one micron with built-in predictive maintenance protocols. J&J uses deep learning for predictive maintenance. SK Walmittal, one of the largest plants in Austria and a European leader in cold-rolled sections, is currently examining a potential use case in cooperation with internal R&D experts. The case in question is the application of deep learning for surface inspection.

5.1. Defect Detection and Classification

Deep learning has limited presence in U.S.-based manufacturing, and the purpose of this article is to provide a necessary understanding of where and how these techniques might be applicable within quality assurance. The results are discussed from an in-depth, exploratory survey of U.S.-based manufacturing establishments that sought to understand the extent of use of different types of inspection, the spread and effectiveness of defect detection and classification within the sampling-based or design of experiments methodologies, the strengths and limitations of human inspectors within the visual-based inspection, the types of false alarms that are prevalent, and the sources of defects. This data is analyzed to shed light on how deep learning might be able to help address some challenges and gaps within the realm of defect characterization and classification, including how to appropriately structure the data.

In manufacturing, a core goal of product testing is defect detection. The objective is to have as few defects as possible. However, in practice, all manufactured products have some susceptibility to fail, and statistics show there are always defects in the production process. Once a defect is identified, the next step is defect classification to associate defects with solutions or interventions. This is usually performed to identify the source of the defect and thus solve or contain the problem. For learning-based approaches for defect identification, the defect detection task may be handled using unsupervised (anomaly detection) or supervised (classification) approaches, while defect classification is typically accomplished through supervised methods. This section details measurements of current defect detection and classification approaches in U.S. manufacturing, as these are critical for understanding where deep learning can and cannot be applied to enhance quality control.

5.2. Predictive Maintenance

At this time, different industries apply predictive maintenance in the hope to optimize their maintenance processes. Industrial use cases for predictive maintenance can be considered as the main drivers of Industry 4.0. One of the main challenges of predictive maintenance consists of the fact that every machine produces vast amounts of data, which are hard to manually assess. By some estimates, about 7 hours per week are being spent on unnecessary maintenance, just to say it is a part of a routine for a lot of enterprises. As a result, the U.S. Department of Energy reports that more than 30% of electricity usage in industry is wasted due to inefficient use and maintenance of equipment.

Deep learning is considered to be more effective for predictive maintenance than expert systems or fuzzy logic. Makus et al divided predictive maintenance using deep learning into three empirical levels: components, system or whole asset level, and fleet level. In terms of components, deep learning is effective for the identification of certain components or their parts, where maintenance is desired. For a system or whole asset, deep learning is employed to identify whether there is a possibility of any machine parts having a shorter remaining useful life (RUL). The main aim of the system or whole asset level is the prediction of at least one type of failure prior to it happening, while there can be multiple deep neural networks working in parallel at this level. Finally, in the case of a fleet, an algorithm assesses the remaining useful life for the entire fleet, while most studies in the available predictive maintenance literature do not focus on the fleet level, working in terms of either component or asset levels.

6. Challenges and Future Directions

There are three critical aspects that need to be overcome in order to expand the application of deep learning in quality assurance for U.S. manufacturing: 1) collection and annotation of high-quality data; 2) accumulation of training samples in order to generalize beyond the particular; and 3) exploring means to explain the prediction or the process based on the deep learning approach (i.e., interpretability and explainability).

The training of the deep learning model must not be limited to the nominal state, but instead must be capable of detecting the full range of defects and anomalous class distributions, which might also involve various defect morphs generated by variations in the manufacturing process conditions and environmental factors. Accumulation of sufficient training cases by time-consuming and expensive data collection should be done in a gated manner over steps: the first collection should address a broad and complete coverage of defect subcategories across the manufacturing process variability. Over time, as the defect experience grows with models that collectively cover all defect subcategories, multiple nets trained on one or a few defect types may be converged into an ensembled net capable of managing the full range of defects with optimal performance. The future fully trained deep learning models may coordinate with other quality assurance tools such as Process Window Index (PWI), Dynamic Machine Capability Index (DMCI), and Statistical Process Control (SPC) to jointly ensure exceptional production quality. Tools under development for impact assessment of "black-box" predictive models including big data model agnostic analytics, sensitivity analysis and model specification curve analysis may be drawn upon to explain deep learning model predictions. Areas for future basic research include exploring active and transfer learning, continual learning, semi-supervised learning and considering the revision of network architecture including temporal learning with convolutional and recurrent neural nets.

6.1. Data Quality and Quantity

Data quality and quantity continue to be a challenge for deep learning, as machines are not capable of such advanced analytical techniques of curating it. Correcting for large, noisy, and strongly harmonic-laden data, especially in real-time scenarios that necessitate the immediate action of maintenance, is one of the core issues that needs solving when considering implementing a deep learning technique for quality assurance in U.S. manufacturing. Simply collecting data creates a massive financial constraint on the manufacturer, on top of the machines being challenged with monitoring every single manufacturing process. A plot of the number of samples listed in section three in different manufacturing processes per industry versus the number of samples users found in research papers about process-based control is documented in figure 1. Another limiting factor related to deep learning and fault detection as a service relates to the irrelevant and vastly more accurate data that must be disambiguated. It is thus vital to incorporate domain knowledge for effective management of all the data and for the effective implementation of this technique.

Six core issues for fault detection as a service with respect to deep learning are: (1) Understanding data from different machines, (2) Disambiguating against irrelevant and vastly more accurate data, typically pointing to real-time related architectures and techniques, (3) Capturing something specific in data that domain experts know, (4) The historical issue of having very little labelled data independent of labelled test data; options to consider include using more popular and easy transferring learning approaches, (5) Noise or reconstruction noise, and (6) Number of hidden layers needed for the deep learning network.

6.2. Interpretability and Explainability

In order to replace domain knowledge or regulatory guidance, deep learning models would need to be able to report their decisions in a transparent and simple way. Small to medium-sized manufacturers, managers of the steel mill, and quality engineers expect to be able to understand what is important in the data to the AI systems, as these are the people our proposed methods are aimed at assisting. Most manufacturers are interested in where decisions come from, rather than having an engineering-oriented explanation that shows flow of data through the neural network.

As has been previously discussed, there are different groups interested in different types of explainability and interpretability. For small to medium-sized manufacturers and process engineers, feature importance with an intuitive explanation is often sufficient for decision making. When the decision the neural network makes needs an explanation that complies with a particular regulatory guideline or, at the very least, something that is more engineering based, then the requirement all of a sudden becomes much more rigorous.

The group that primarily decides if system explanations are valid, however, are interested in process level knowledge where they can see that the process is conforming to its expected behavior, so they prefer a rare event to be used in an unusual way, such as novelty detection or one-class classification. Policymakers, the government, and minority populations have a different view of what is considered explainable. Policymakers both in the government and at Alpine Electronics prefer a personalized explanation to be explainable, and suggest that all people need to be treated equally by a system.

3.2. Trustworthiness

Deep learning models will need to serve diverse stakeholders, many of whom have little AI experience. For a common person or small business, reliability of a model is much more important than top accuracy or state-of-the-art results. In practical application, stakeholders demand to have confidence in the model. For the reliability aspect, making confidence bounds that are easy to use and calculate is an effective way. This is technically complex, so is often not done, but would be a significant innovation if developed.

The four potential aspects of validity are classical criteria, but for applications where the stakes are particularly high they often have to be even more stringent than one would wish or expect, which is particularly challenging in the context of US regulatory requirements. Of critical value is the timeliness and predictive ability of the measurement methods. Juried consensus methods for evaluation of data validity currently are not strongly in favor of AI algorithms, but already are showing signs of change, and could eventually welcome them for hypothesis development. However, new regulatory development in the EU, namely the "precautionary principle," would be more favorable to use of AI in some situations.

7. Conclusion

In conclusion, deep learning is helpful in identifying potential defects in wheels and forges, which makes it possible to detect and identify defects that end up being sold to millions of customers without even the factory recognizing the defects despite checking the end products. This new use of deep learning can help to improve the quality of U.S. manufacturing and revitalize the U.S. manufacturing industry. It can also bring significant economic benefits to U.S. manufacturing companies that adopt these new ideas and technologies, with each dollar invested in quality assurance bringing more than 10 times this investment in discounted profits into the future.

In the future, I will bring new algorithms and deep learning technologies to help machines identify the composition of raw materials between 1500 °C and 2000 °C, operate and control these technology development results on multiple levels of deep learning to improve the quality and energy efficiency of the electric arc furnace, and improve the overall production process of U.S. manufacturers in order to be able to compete internationally. Our technology will bring many applications to U.S. manufacturers in the form of collaborative work and joint investment. Our research and our method showcase the exciting potential of integrating deep learning-based techniques into quality assurance in U.S. manufacturing. The application of these techniques in applications such as wear and forge wheels for U.S. railroads presents an opportunity for the next few years.

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