A seminar report on

Application of IoT and Machine Learning in Metal Forming Industry

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Abstract

Machine learning is one of the most highly actively researched and sought after topic in recent times. There are areas in Mechanical Engineering field where we can apply Machine Learning to automate the process. One of the domain is Manufacturing where we can use Machine Learning to Design for Manufacturing, inverse modelling, fault prediction and defect inspection, logistic management to avoid the errors caused by humans in each of these phase. This report contains different applications of machine learning and IoT in metal forming industries and current trend industries and researchers are working upon.

1. Introduction

Machine Learning and the Internet of Things is like a match made in Tech Heaven. According to Business Insider, there will be more than 64 billion IoT devices by 2025, up from about 9 billion in 2017. All these IoT devices generate a lot of data that needs to be collected and mined for actionable results. Now, this requires the expertise of advanced Machine Learning models that are based on deep neural networks.
So the Internet of Things is used to collect and handle the huge amount of data that is required by the ML algorithms. In turn, these algorithms convert the data into useful actionable results that can be implemented by the IoT devices. This convergence of IoT and ML can transform industries and help them in making more informed decisions based on the mammoth data available every day which will result in new value propositions, business models, revenue streams and services.

Just as electricity transformed almost everything 100 years ago, today I actually have a hard time thinking of an industry that I don't think Artificial Intelligence and Machine Learning will transform in the next several years – Andrew Ng

Machine Learning (ML) is a sub-field of computer science that evolved from the study of Pattern Recognition and Computational learning Theory in artificial intelligence.[1] In simpler terms: It uses algorithms that iteratively learn from data and allows computers to discover patterns without being explicitly Programmed where to look. ML is nothing but an ability of Computers to learn from data or past experience. The data comes from various sources such as sensors, domain knowledge, experimental runs, etc [1]. It helps to make intelligent predictions or decisions based on the data. Machine Learning refers to a broad family of algorithmic techniques which take advantage of historical data to learn behaviors, patterns, and functions to provide useful inference in a variety of scenarios. They attempt to learn by examples and are capable to capture complex relationships among collected data that are hard to describe, hence such methods are suitable for situations where physics-based modelling is not favourable to replicate behavior model [1]. Depending on the type of available data, learning can be performed in different ways as follows [1]:

• Supervised (inductive) learning: Training data includes desired outputs i.e., data are composed of input and the desired output is known. Such data is also called as labelled data.

• Unsupervised learning: Training data does not include desired outputs i.e. learning data are only composed of input. Such data is also called as unlabelled data. The data is analyzed and studied through clustering, reduce the dimensionality, etc into a different class.

• Reinforcement learning: It is about taking suitable action to maximize reward in a particular situation.

The main problem with Machine learning is that it requires extensive data set to train the algorithm for future prediction. Machine learning algorithms work on specific problems only, if there is any different test case then there are chances that the ML algorithm will fail [1]. It is not a guarantee that machine learning algorithms will always work in every case imaginable. Sometimes or most of the times machine learning will fail, thus it requires some understanding of the problem at hand in order to apply the right machine learning algorithm. Bias in the data has significant impact on the accuracy of the model [11].

Although the term IoT is only 20 years old the concepts behind it are from long. In the year 1964 Karl Steinbuch a german scientist said “In few decades of time computers will interwoven ino almost every industrial products”. From then after 25 years first few product of IoT were noted like a toaster connect to internet a coca cola dispensing machine showing data about how much quantity is left over the internet. By this time the term IoT was not coined yet. It was used for the first time by Kevin Ashton in his presentation while introducing the RFID technology connected to internet to his higher management. But the term IoT was not much known till 2009 when it was announced that more things are connected to internet than the number of people connected to internet. Then the next big event took place when internet moved from IPv4 to IPv6. This is also the same time when the full potential of deep learning was being realised both due to increased computational power and used of new activation function which made the gradient decent optimization possible[2].

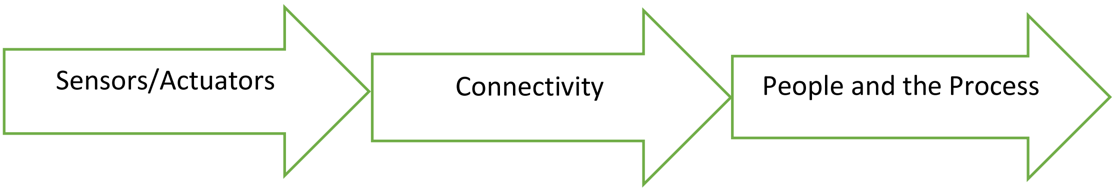
This report tried to cover basics of IoT and Machine learning as and when required during the review of certain application. This report is divided into three phases like Application of IoT, Application of Machine Learning and Combination of both the technologies. Application of Machine Learning is further divided into preproduction stage, production stage and post production inspection.

2. Internet of Things

In its special report on internet of Things issued in March 2014 IEEE described IoT as

"A network of items-each embedded with sensors which as connected to the internet"

Its has mainly three components



2.1 IoT Architecture

IoT architecture is the system of numerous elements: sensors, protocols, actuators, cloud services, and layers. Given its complexity, there exist 4 stages of IoT architecture. Such a number is chosen to steadily include these various types of components into a sophisticated and unified network[2].

- Sensors and actuators.
- Internet getaways and Data Acquisition Systems.
- Edge IT.
- Data center and cloud.

Sensors and Actuators are called ground level devices. Sensors collect the data in its analog form from the surface they are deployed on. These are at the site of interest. Actuators are option in an IoT system. If we want to take any action from remote location depending on the data displayed to us on the cloud then these come into picture.

Sensor then send the data to **Internet Gateway**. These are basically high power devices unlike sensors. These collect the data convert then into digital form and pre-process then into. Gate are placed close to the sensors because our IoT modules are generally low power low range devices. So the data to reach gateways distance needs to be small.

Before storing the data on the cloud data is again pre-processed to avoid overhead data which is attached with each data sent from gate to cloud containing information about the internet protocols used which is of no interest to us once data reaches the cloud. This analytics part which takes place before storing in cloud is called **Edge Computing**.

Cloud storage is where actual insightful analytics is being done. Not only for the current operation but for future use as well[2].

Communication between ways stages of architecture is key for efficient working of the IoT system. As the Internet of Things is growing very rapidly, there are a large number of heterogeneous smart devices connecting to the Internet. IoT devices are battery powered, with minimal compute and storage resources. Because of their constrained nature, there are various communication challenges involved, which are as follows:

(1) Addressing and identification: since millions of smart things will be connected to the Internet, they will have to be identified through a unique address, on the basis of which they communicate with each other. For this, we need a large addressing space, and a unique address for each smart object.
(2) Low power communication: communication of data between devices is a power consuming task, specially, wireless communication. Therefore, we need a solution that facilitates communication with low power consumption.
(3) Routing protocols with low memory requirement and efficient communication patterns.
(4) High speed and non-lossy communication.

IoT devices typically connect to the Internet through the IP (Internet Protocol) stack. This stack is very complex and demands a large amount of power and memory from the connecting devices. The IoT devices can also connect locally through non-IP networks, which consume less power, and connect to the Internet via a smart gateway. Non-IP communication channels such as Bluetooth, RFID, and NFC are fairly popular but are limited in their range (up to a few meters)[3].

2.2 IIoT

IIoT stands for the Industrial Internet of Things or Industrial IoT that initially mainly referred to an industrial framework whereby a large number of devices or machines are connected and synchronized through the use of software tools and third platform technologies in a machine-to-machine and Internet of Things context, later an Industry 4.0 or Industrial Internet context.

In the pure machine-to-machine and Industry 4.0 context, the advantage of the frameworks and systems that IIoT refers to, is that they can operate semi-independently or with very minimal human intervention[17].

Such systems will increasingly be able to intelligently respond and even change their course of action based on the information received through the feedback loops established within the framework.

The idea behind machine-to-machine communication is to reduce human interventions as much as possible so that the highest level of automation could be achieved. If we look at the concept of the Internet of Everything, this M2M dimension of the Industrial Internet of Things happens within the sphere of the things as you can see in the original depiction of the Internet of Everything by Cisco[17].

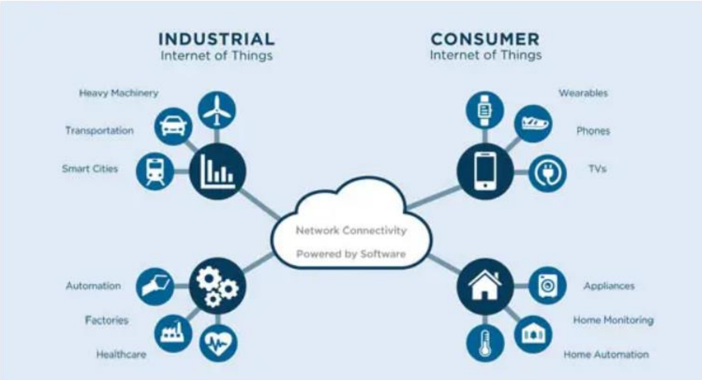


FIGURE 1 DIFFERENCE BETWEEN INDUSTRIAL AND CONSUMER INTERNET OF THINGS[17]

FIGURE 2 BENEFITS OBSERVED IN VARIOUS FIELD DUE TO IIOT[17]

2.3 case study

Manufacturers in the metal forming industry are paying attentions on smart manufacturing with the internet of things (IoT). An innovation has been occurring by changing metal forming processes from analog to digital by utilizing servo press system and IT technology for improving worth of the mass production manufacturing technology. Initiatives of process visualization using die-embedded sensors and data management with the IoT are also under progress[5].
The servo press has controllability as a digital processing technology, and has high potential capability to improve formability of working materials and accuracy of products by utilizing various slide motions . However, It is only the dawn of servo press application technology, and in order to derive its high potential, it is necessary to develop peripheral element technologies such as design of die and selection of lubricant suitable for servo press. Furthermore, in order to realize the smart manufacturing with the servo press advanced control technology, process monitoring technology, data processing technology and network technology are also essential element technologies[5].

Different servo motor motions are used for better formability, better product dimensions etc. depending on the material under consideration.

- Pulse Motion
- Step Motion
- Constant speed(most primitive)

Although metal forming with servo press has advantages in increase of forming limit, higher product accuracy, the utilization of the servo press is still limited and design of the slide motion needs experiences and knowledges. Furthermore, more information is necessary to understand phenomena in the process while using various slide motions and to design the motions to adapt to different shape of products with different materials. In addition to process simulation technology, process sensing becomes more important for the servo press applications, and it is a big challenge to monitoring the phenomena occurring in the dies since deformation of the workpiece, contact states with the die are complicated and the interface between the dies and the material is under a high pressure state. An integral process visualization technology is expected by development of die embedded sensors and integration with computer simulation and it will promote advancement of servo press utilization technology more rapidly, leading to smart forming process[5].
To make it easier for users to use these kind of die embedded sensor, a bolt type sensor, in which piezo sensor was built in a bolt that can be used to fasten die instead of normal bolt, has been developed and commercialized. Other monitoring system using die embedded sensors, such as ultrasonic sensors for detecting contact between die and specimen, AE (Acoustic emission) sensor for sliding friction, and micro displacement sensor for shearing force measurement and other sensors, are developed and expected to be utilized in forming process[5].

In a precise cold forging of 2-stage cycloid gears, fully automated production line including upper step and lower step was developed. Fig 3 outlines its fully automated production line: management of the state of all processes on-line, applying various information of the upper process to the forging process conditions, and further applying the information of the forging process to the downstream finishing process. The information of each process including cold forging is unified and visualization of the process is realized by controlling the individual part precision and it is useful for process management, quality control, especially traceability. Application of process design support technology and network technology to press processing machine automatically manages machining data which recorded complicated servo motion programmed processing condition and production time information of each product for each product. By doing so, digitization of production system management has been realized. In addition, we have created a number of processing expertise accumulated so far in DB, so even beginners of servo press can make optimal motion selection for each process type. In addition, machine makers collaborated with cloud management companies, the sheet metal processing support system was developed with IoT shown in Fig 4, processing data collection, die management, motion creation support can be done online, unified management by data cloud And support press processing support for maintenance and processing to users. This is the realization of the. Connected factory for a sheet metal forming[5].

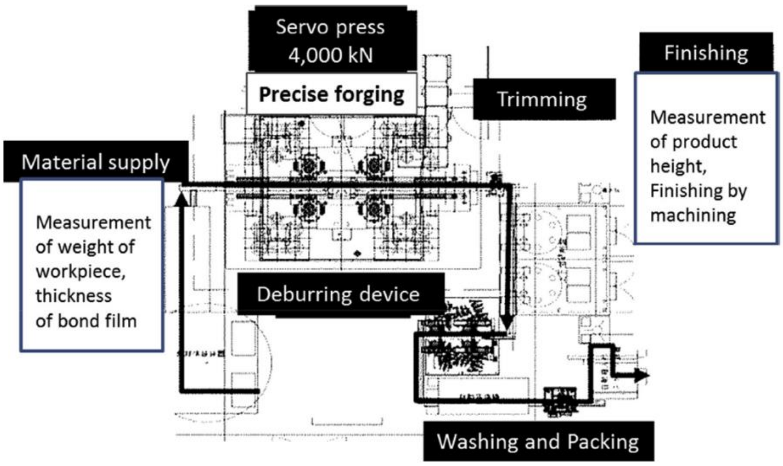


FIGURE 3 AUTOMATED PRODUCTION LINE FOR CYCLOIDAL GEAR

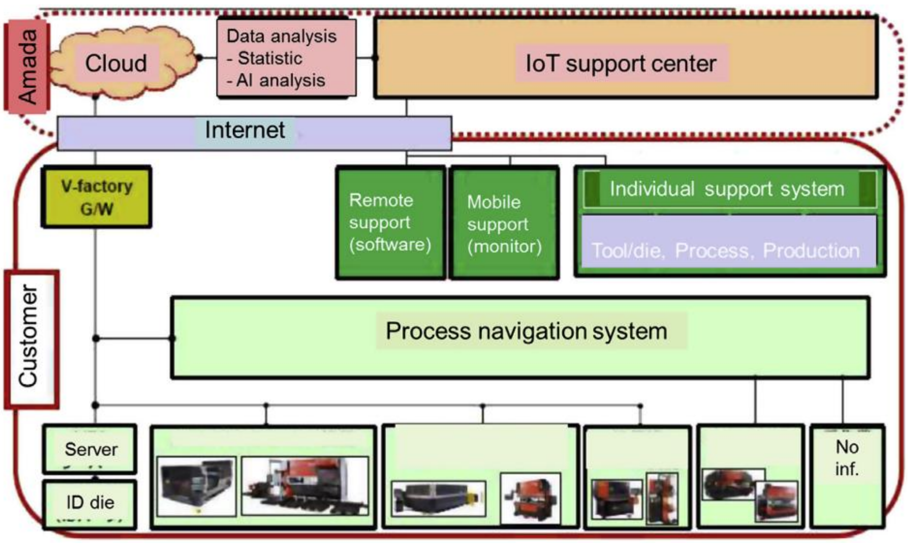


FIGURE 4 IoT SUPPORT SYSTEM FOR SHEET METAL FORMING PROCESS

3. Machine Learning

This section is divided futher as 3 stages of forming industry. One in before production like design phase or the stage where process to be used to manufacture the designed part is decided. Then during production like how inverse problems can be solved using ML algorithms them finally post production how can these ML be used for better fault inspection.

3.1 Pre Production Phase

In this study, a machine learning approach was used for the first time to identify the manufacturing process that formed a part solely from the final geometry. Presently it is being done by following guidelines specific to a industry and is usually proprietary. Complex classification tasks usually contain nonlinear and inaccessible relationships in their data making them extremely difficult to tackle using a rule-based approach. For example, facial recognition originally was a rule-based approach. It uses features like nose eyes etc to recognise the person. For that we need the person to be at the centre of the frame facing towards camera. Here comes the importance of learning-based approach which does not require before mentioned characteristics nor does it require us to know how it does the trick. Geometry description is a fundamental step in many of the papers named above and in any automated version of metal sheet design and manufacturing. For the purposes of this study, data were generated algorithmically based on textbook and practical knowledge of geometries resulting from specific pro-cesses. They choose five sheet forming processes for this project, namely, Spinning, Deep Drawing, Stretch forming, Air Bending, Roll Bending. Function were written mostly in the form of Bezier curve to replicate geometries which can be manufactured by each of these processes[6].

3.1.1 Data Generation Method

NN's require large number of data points to be trained effectively. Part geometries are produced as cloud of points representing surface with no variation in thickness. For each of the processes 300 sample geometries were produced, each described by 10,000 points.

Shear spinning:

Geometries were produced using

$$p(t) = (1-t)^3 \otimes pt_1 + 3(1-t)^2 \otimes pt_2 + 3(1-t)t^2 \otimes pt_3 + t^3 \otimes pt_4$$

Where product is the Kronecker product and the four points defining the curve are

$$pt_1 = \begin{bmatrix} 0 \\ r_1 \end{bmatrix}, \quad pt_2 = \begin{bmatrix} r_2 \\ r_3 \end{bmatrix}, \quad pt_3 = \begin{bmatrix} r_4 \\ r_3 \end{bmatrix}, \quad pt_4 = \begin{bmatrix} 10 \\ r_5 \end{bmatrix}.$$

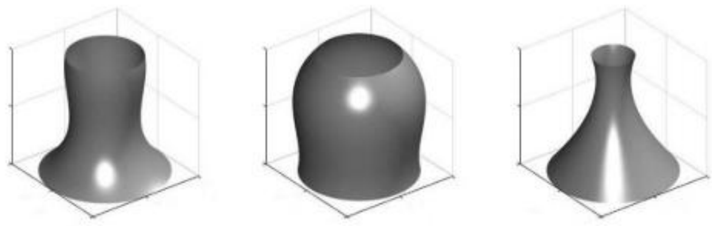


FIGURE 5: SHEAR SPINNING GEOMETRIES[6]

Deep Drawing:

Geometries were produced using extruding a circle i.e to create a cylinder. Complex assymetric shapes were produced using a flat surface at different orientations and a curved surface formed from sinusoidal functions and subtracting both.

$$z = r_6 - \frac{1}{2}\left(r_{7a}\cos\left(r_{8a}x/10\right)^{r_{8b}} + r_{7b}\sin\left(r_{8c}y\right)^{r_{8d}}\right),$$

FIGURE 6: DEEP DRAWING GEOMETRIES[6]

Similarly, shapes were defined for other profiles.

3.1.2 Geometric Representation

Different manufacturing process develop different geometric feature. The information about the geometric features is not only given by the point cloud as described above but also in the curvature at each point. Four different curvatures were test and compared namely **Principal curvature**, **mean**, **Gaussian** and combination of **Mean and Gaussian**[6].

3.1.3 Neural Network Architecture

Neural network architecture were used to classify the model. Initially Shallow networks were used and found that they classify inputs based on absolute magnitude, relative magnitude and position within the input space. On the other hand Convolution neural networks which are deep neural networks having multiple layers which increase the variety of features found and also make the model scale and orientation independent. CNN typically has following layers.

Convolution layer: This layer applies convolutional filters to the input. By splitting the input into subregions, mathematical operations can be performed on local regions of the input to produce a single value corresponding to a specific feature at a specific location in the input.

ReLU layer: The Rectified Linear Unit layer applies an activation function to produce non-linearities in the model.

Max pooling layer: The max pooling layer down-samples the input to reduce dimensionality by keeping the maximum value of different subregions and discarding all other values. Max pooling is critical for DNNs as it decreases processing time.

Fully connected layer: Dense (fully connected) layers per- form classification on the features extracted and down- sampled by the convolutional and pooling layers.

Softmax layer: The softmax function is usually the last layer of a NN-based classifier and is used to provide a probability for each possible label in the output layer[11].

Geometry representation method	Accuracy (%)	Confidence margin (%)
Principal curvatures	79.3	26.2
Gaussian curvature	73.4	21.3
Mean curvature	54.2	23.7
Gaussian and mean curvatures	41.3	24.8

FIGURE 7: COMPARISON OF DIFFERENT GEOMETRIC REPRESENTATION[6]

	Configuration 1		Configuration 2		Configuration 3	
Geometry representation method	Accuracy (%)	Confidence margin (%)	Accuracy (%)	Confidence margin (%)	Accuracy (%)	Confidence margin (%)
Principal curvatures	73.2	79.9	78.9	81.6	77.6	81.0
Gaussian curvature	63.3	61.3	65.6	48.1	68.0	60.3
Mean curvature	65.7	56.3	66.6	48.3	64.2	64.6
Gaussian and mean curvatures	85.6	82.0	86.3	72.2	88.8	87.6

FIGURE 8: COMPARISON OF DIFFERENT ARCHITECTURES

In this paper they worked on only five forming processes now there is a research gap to include more processes and also a component might require more than one manufacture process to get completed which also can be incorporated in future work.

3.1.4 Design for manufacturing

Within the Transregional Collaborative Research Centre 73, a self-learning engineering workbench is being developed. It assists product developers in designing sheet-bulk metal formed (SBMF) parts by computing the effects of given product and process characteristics on the product properties. This contribution presents a novel approach to using deep learning methods for the properties prediction. By making use of a parameter study of 20 SBMF part designs, a metamodel is trained and used to predict the total equivalent plastic strain on local level as an indicator for part manufacturability[7].

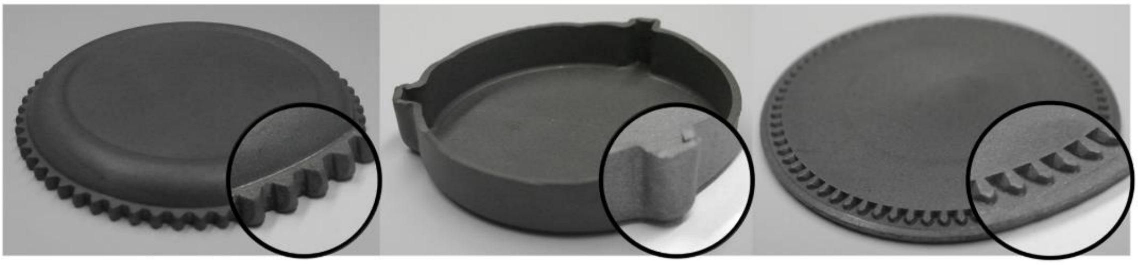


FIGURE 9:EXAMPLE OF PARTS BEING USED IN TRAINING

Parameters like height and width of different features of the component were varied and simulations were performed. Now the total equivalent plastic strain at each node of the mesh were noted in the format as below[7].

	Node ID	X-coordinate	Y-coordinate	Z-coordinate	TEPS
Type	*Integer*	*Floating point number*			

This structured data is feed as input to the deep neural network model and TEPS at each local region or feature is predicted.

3.2 Production Phase

An inverse model for a sheet metal forming process aims to determine the initial parameter levels required to form the final formed shape. This is a difficult problem that is usually approached by traditional methods such as finite element analysis. Formulating the problem as a classification problem makes it possible to use well established classification algorithms, such as decision trees. Classification is, however, generally based on a winner-takes-all approach when associating the output value with the corresponding class[8].

On the other hand, when formulating the problem as a regression task, all the output values are combined to produce the corresponding class value. For a multi-class problem, this may result in very different associations compared with classification between the output of the model and the corresponding class. Such formulation makes it possible to use well known regression algorithms, such as neural networks[8].

A neural network based inverse model of a sheet forming process was developed, and compare its performance with that of a linear model. Both models are used in two modes, classification mode and a function estimation mode, to investigate the advantage of re-formulating the problem as a function estimation[8].

This results in large improvements in the recognition rate of set-up parameters of a sheet metal forming process for both models, with a neural network model achieving much more accurate parameter recognition than a linear model[8].

	MLP	Linear Regression
Blank Holding Force	100%	98.5
Die Radii	98.5	95.6
Tool Gap	92.6	83.0

Given the similar prediction accuracies from analysing forging data [15] it may be generalised that the PDM shape error metric will provide reasonable classification data in most cases for other shape manufacturing processes. Moreover, this shape process parameter model allows the further development of automated intelligent process control within sheet metal forming by providing a mechanism that can recognize how distant the current set-up parameters are from the optimal parameter setup in order to produce the desired geometric shape[8].

3.2.1 Incremental Forming

ISF is highly complex process which has highly complex parameters to deal with like tool path, tool speed, material properties to overcome various issues faced by the process. Issues faced exist because we are trying to form a part without without using specify die. This process is less accurate than other more specific operations like deep drawing which need a specialized tooling and die system for its product resulting in better accuracy. There are various factors which reduce the forming part accuracy like

- Forming machinery’s structural compliance
- Forming machinery’s positioning accuracy

- Sheet metal's spring back
- Sheet metal's subsequent deformation
- Sheet metal's bulging Forming strategy

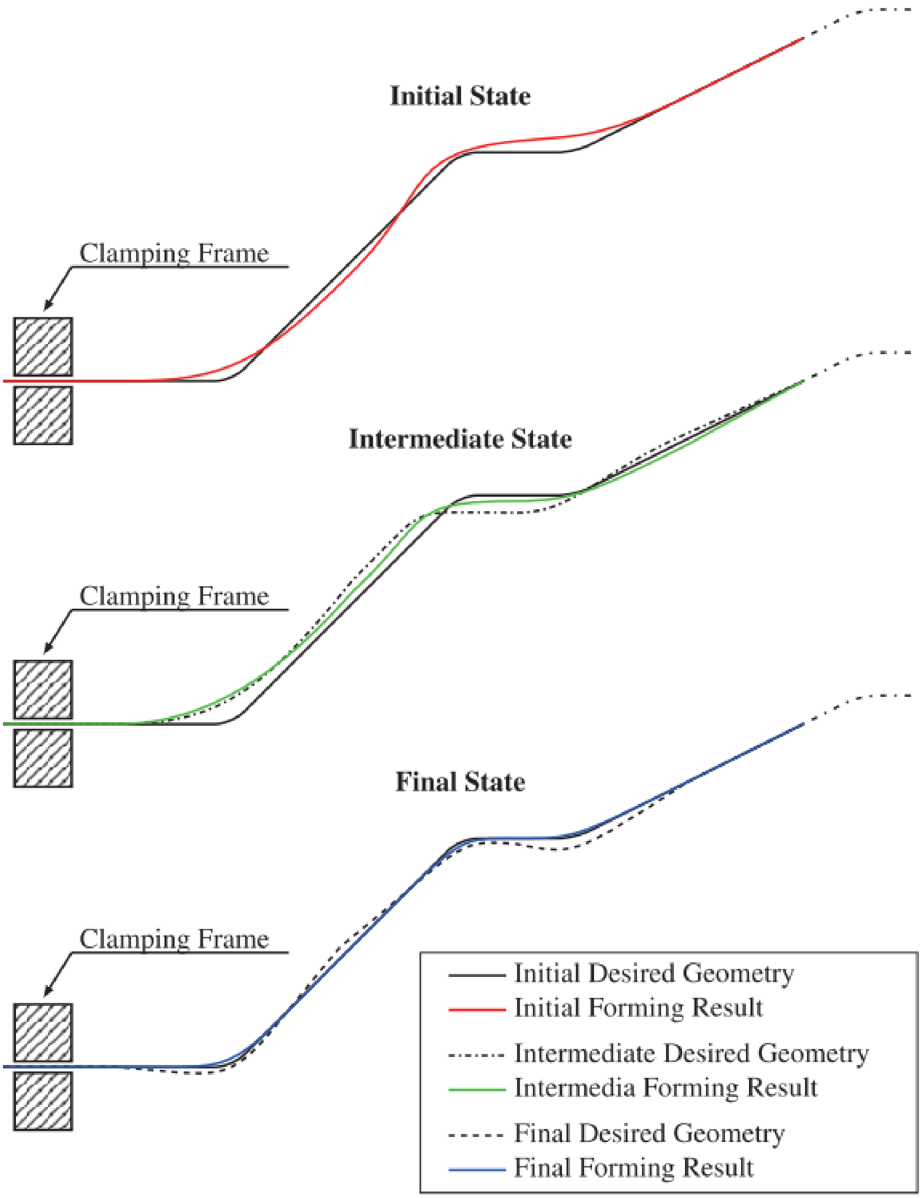


FIGURE 10: VISUALIZATION OF THE LEARNING PROGRESS OF THE RL APPROACH. IN EVERY SUBFIGURE THE INITIAL DESIRED GEOMETRY, A MORPHED GEOMETRY WHICH IS USED FOR PATH PLANNING WITHIN THE LEARNING STATE AND THE ACCORDING FORMING RESULT ARE ILLUSTRATED.

Prior to this work in the field of ISF many other ways were adopted to make the process more efficient. Like used of ANN to predict tool path and reduce the spring back by optimisinf the step size in the tool path. Further more, ANNs are used to predict the formability and failure of sheet metal workpieces as well as the process performance of the ISF process[9].

3.2.1 CAD and PLM

With the increasing amount of available data, computing power and network speed for a decreasing cost, the manufacturing industry is facing an unprecedented amount of data to process, understand and exploit. Phenomena such as Big Data, the Internet-of-Things, Closed-Loop Product Lifecycle Management, and the advances of Smart Factories tend to produce humanly unmanageable quantities of data. However, due to massive data scale, these opportunities all require to be, at least partly, automated. Recurring issues such as massive amounts of data, high data-dimensionality, heterogeneous data aspects, and low data-quality greatly reduce, not only data integration and consumption, but also automation possibilities for statistical analysis[10].

DMU-Net Data set was prepared to identify different mechanical parts. The dataset consist of 30 different classes with varying number od parts in each case. This dataset is prepared for research purpose of object detection. Our model could be trained on these cad models and learn qualitatively to identify the object. Later this model could be used in automated assembly lines to inform the concerned workstation to take appropriate action. This Data set was developed for researcher to accommodate different types of data like a 2D drawing of the object, 3D cad model or, 2D image of the object which are the general ways of transferring knowledge inside the manufacturing environment[10].

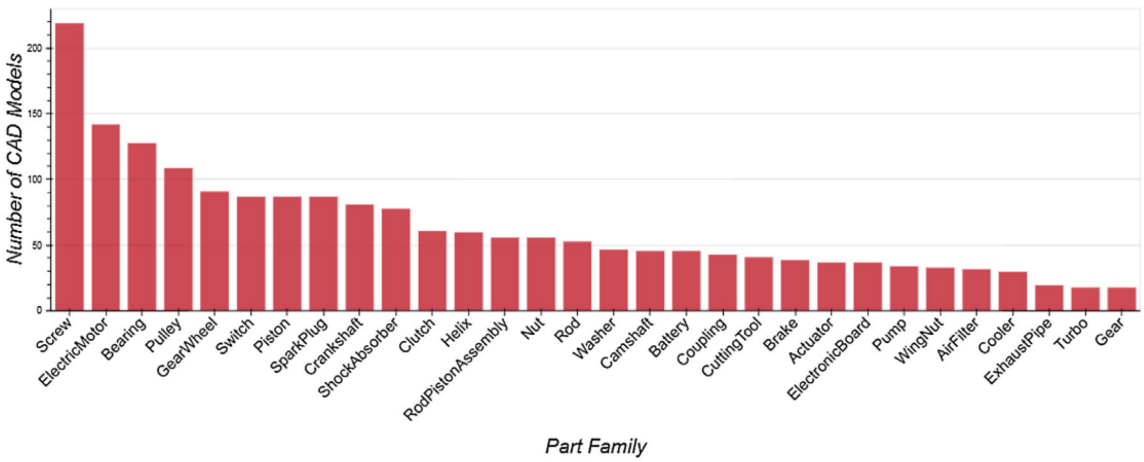


FIGURE 11: DMU DATA SET DISTRIBUTION[10]

		3-Stratified fold cross validation		Testing set	
Model name	Transfer learning	Top-1 accuracy	Top-5 accuracy	Top-1 accuracy	Top-5 accuracy
Random guess	Irrelevant	1/30 = 3.3%	5/30 = 16.67%	1/30 = 3.3%	5/30 = 16.67%
LeNet-5 [102]	No	14.66%	24.99%	7.4%	18.34%
AlexNet [37]	No	63.96%	92.05%	34.67%	61.15%
AlexNet [37]	Yes	58.73%	84.35%	52.50%	73.23%
GoogLeNet [103]	No	90.17%	97.51%	51.76%	67.59%
GoogLeNet [103]	Yes	84.35%	93.48%	82.81%	90.68%

FIGURE 12: EFFECT OF TRANSFER LEARNING[10]

In contrast with classical machine learning where domain experts preprocessed the data by extrcating the important features, deep learning models are able to extract data by them selfs from unstructured data.This is another important property because of which manufactures can quickly adopt to any change in the process without actually getting into the physics of it. To handle data in different format and different data type. Embedded structures and Autoencoder can be helpful[10].

3.3 Post Production

This research investigates detection and classification of two types of the surface defects in extruded aluminium profiles; blisters and scratches. An experimental system is used to capture images and appropriate statistical features from a novel technique based on gradient-only co-occurrence matrices (GOCM) are proposed to detect and classify three distinct classes:

- non-defective
- blisters
- scratches.

Other type of defect found in the literature are blisters, die-lines, pick-up, tearing, color streaks, weld lines, black lines and scratches[12].

The developed methodology makes use of the Sobel edge detector to obtain the gradient magnitude of the image (GOCM). A comparison is made between the sta- tistical features extracted from the original image (GLCM) and those extracted from the gradient magnitude (GOCM). This paper describes in detail every step of the image processing with example pictures illustrating the method- ology. The features extracted from the image processing are classified by a two-layer feed-forward artificial neural network. The artificial neural network training is tested using different combinations of statistical features with different topologies. Features are compared individually and grouped. This achievied upto 98.6 % total testing accuracy[12].

Co-occurance matrix is calculated as :

$$C_(\Delta x, \Delta y)(i, j) = \sum_{p,q=1}^{N,M} \begin{cases} 1 & \text{if } I(p, q) = i \quad \text{and} \\ & I(p + \Delta x, q + \Delta y) = j \\ 0 & \text{otherwise} \end{cases}$$

where i and j are the image intensity values, p and q are the spatial positions in the image I and the offset (Δx, Δy) depends on the direction θ used and the distance d at which the matrix is computed. Properties are such as Contrast, Homogeneity, Energy and Correlation are derived from co-occurrence matrices[12].

Contrast, measures the intensity contrast between neighboring pixels.

Homogeneity measures the closeness of the distribution of elements in the co-occurrence matrix to its diagonal.

Energy calculates the sum of squared elements in the co-occurrence matrix.

Correlation measures the linear dependency of grey levels on neighboring pixels.

A recent research on aluminium surface quality inspection was performed by Garbacz and Giesko. In this research, without publishing any results, they discussed about possible ways of detecting defects with a strong emphasis on surface temperature distribution via an infrared camera. On a similar subject, Caleb-Solly and Smith have created an adaptive surface inspection system via interactive evolution. The systems was applied in the hot-rolled steel industry and amongst the techniques used are image segmentation, self organizing map. neural network, multi-layer perceptron classifier and evolutionary algorithms[12].

Severstal is leading the charge in efficient steel mining and production. They believe the future of metallurgy requires development across the economic, ecological, and social aspects of the industry—and they take corporate responsibility seriously. The company recently created the country’s largest industrial data lake, with petabytes of data that were previously discarded. Severstal is now looking to machine learning to improve automation, increase efficiency, and maintain high quality in their production.
The production process of flat sheet steel is especially delicate. From heating and rolling, to drying and cutting, several machines touch flat steel by the time it’s ready to ship. Today, Severstal uses images from high frequency cameras to power a defect detection algorithm. They held a competition on Kaggle to improve the algorithm with prize money worth $120000. That how much profit they expect to earn through this[12].

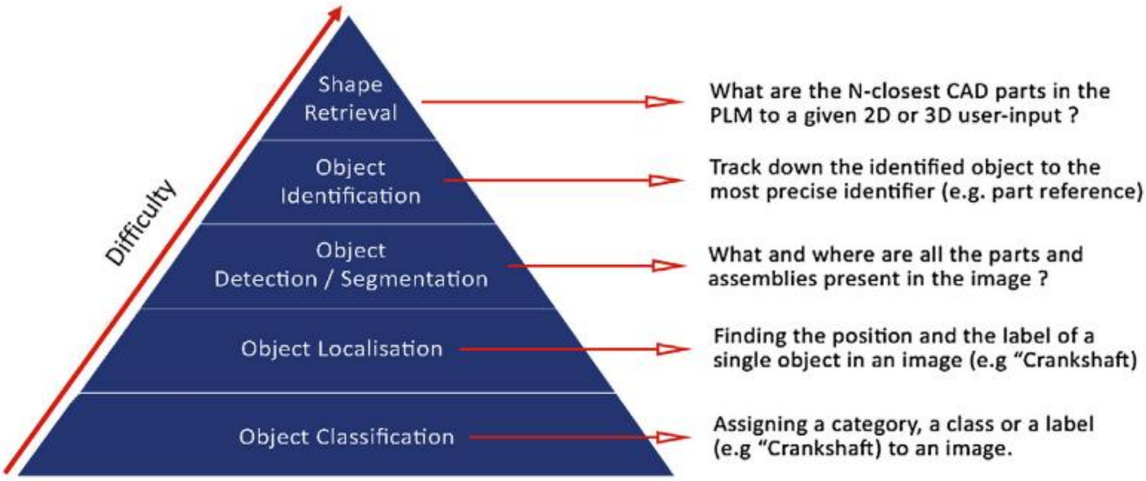


FIGURE 13 VARIUOS STAGES OF VISUAL INSPECTION

Various startups and industries are working in this direction like Gryffin Robotec, CodeGlobal, landing.ai to name a few.

4.Dealing with Data scarcity

As manufacturers begin to integrate AI solutions into production lines, data scarcity has emerged as a major challenge. Unlike consumer Internet companies, which have data from billions of users to train powerful AI models, collecting massive training sets in manufacturing is often not feasible[15].

For example, in automotive manufacturing, where lean Six Sigma practices have been widely adopted, most OEMs and Tier One suppliers strive to have fewer than three to four defects per million parts. The rarity of these defects makes it challenging to have sufficient defect data to train visual inspection models.

Big data has enabled AI in consumer internet companies. Can manufacturing also make AI work with small data? In fact, recent advances in AI are making this possible. Manufacturers can use the following techniques and technologies to circumvent the small data problem to help their AI projects go live even with only dozens or fewer examples

Synthetic data generation is used to synthesize novel images that are difficult to collect in real life. Recent advances in techniques such as GANs, variational autoencoders, domain randomization and data augmentation can be used to do this.

Transfer learning is a technique that enables AI to learn from a related task where there is ample data available and then uses this knowledge to help solve the small data task. For example, an AI learns to find dents from 1,000 pictures of dents collected from a variety of products and data sources. It can then transfer this knowledge to detect dents in a specific novel product with only a few pictures of dents.

Self-supervised learning: Similar to transfer-learning. but the obtained knowledge is acquired by solving a slightly different task and then adapted to small data problem. For example, you can take a lot of OK images and create a puzzle-like grid to be sorted by a base model. Solving this dummy problem will force the model to acquire domain knowledge that can be used as starting point in the small data task.

In ***anomaly detection,*** the AI sees zero examples of defect and only examples of OK images. The algorithm learns to flag anything that deviates significantly from the OK images as a potential problem.

Hand-coded knowledge is an example in which an AI team interviews the inspection engineers and tries to encode as much of their institutional knowledge as possible into a system. Modern machine learning has been trending toward systems that rely on data rather than on human institutional knowledge, but when data isn't available, skilled AI teams can engineer machine learning systems that leverage this knowledge.

In ***few-shot learning,*** the small-data problem is reformulated to help the AI system to learn an easier, less data hungry inspection task while achieving the same goal. In this scenario, AI is given thousands of easier inspection tasks, where each task has only 10 (or another similarly small number) examples. This forces the AI to learn to spot the most important patterns since it only has a small dataset. After that, when you expose this AI to the problem you care about, which has only a similar number of examples, its performance will benefit from it having seen thousands of similar small data tasks[15].

5. Combination of IoT and ML in predictive Maintenance

It's a timeless manufacturing goal: to produce high quality products at minimum cost. Factory 4.0 is already demonstrating its value by enabling manufacturers to reach this goal more successfully than ever, and one of the core technologies driving this new wave of ultra-automation is Industrial AI and Machine Learning[16].

Data has become a valuable resource, and it's cheaper than ever to capture and store. Through the use of artificial intelligence, specifically Process-Based Machine Learning, manufacturers can use data to significantly impact their bottom line by greatly improving production efficiency, product quality, and employee safety. Maintenance represents a significant part of any manufacturing operation's expenses. For this reason, Predictive Maintenance has become a common goal amongst manufacturers, drawn by its many benefits including significant reductions in the impact of the Six Big Losses. While certain manufacturers do perform Predictive Maintenance this is traditionally been done using SCADA systems set up with human-coded thresholds, alert rules and configurations. This semi-manual approach doesn't take into account the more complex dynamics behavioural patterns of machinery, or the contextual data relating to the manufacturing process at large. For example, a sensor on a production machine may pick up a sudden rise in temperature. A static rule-based system would not take into account the fact that the machine is undergoing sterilization, and would proceed to trigger a false-positive alert. In contrast, Machine Learning algorithm are fed OT data(from the production floor: sensors, PLCs, historians, SCADA), IT data(contextual data: ERP, qualities, MES, etc), and manufacturing process information describing the synchronicity between the machines and the rate of production flow. In industrial AI, the process known as training, enables the ML algorithms to detect anomalies and test correlations while searching for patterns across the various data feeds. The power of machine learning lies in its capacity to analyse very large amounts of data in real tim, and propose actionable response to issue that may arise. The health and behaviour of every asset and system are constantly evaluated, component deterioration is identified is identified prior to malfunction, and insights visualized on digital twin[16].

6. M.Tech Project Proposal

The quality of molded products are the result of multiple machine, material and process parameters. As need for control of the injection molding process is high, the first step in this case is to precisely design, measure and monitor the process to make the key process variables observable and controllable[14].

The process of injection molding includes four main stages: plasticization, injection, cooling and ejection. Among these four, the cooling stage takes from 50% to 80% of the cycle time. Many optimization techniques and simulation-based studies are being in use for obtaining optimal process parameters for conducting injection molding process and obtaining product with highest quality. still there is a question mark on their practical utility as due to variation during molding cycles, quality failures occur. Quality consistency and stable processing conditions are a common problem for injection molding process due to non-uniform variations in the molding machine after several cycles. The quality of final product depends on all the parameters involved in molding process. Then relation between parameters that can and cannot be measured can be described through application of modelling and formulas. After building standard value and establishing interrelationship between sensor signals, and machine input parameters, study is focused on real time monitoring and control. A learning algorithm is setup with the mindset of generating machine input parameters for corresponding compensation in sensor readings and hence the product quality. Approches to minimise quality defects like warpage, shrinkage and flashes. These approaches include the Model based classical control, Taguchi techniques, Artificial neural networks (ANN), Fuzzy logic, Genetic Algorithms, Support Vector Machines, Case Based Reasoning are being in use for process parameters optimization. Process monitoring for injection molding using nozzle-based pressure and temperature sensors has also been explored. Adaptive process control has also been utilized for self-learning control which utilizes data acquisition, data mining and knowledge-building models[14].

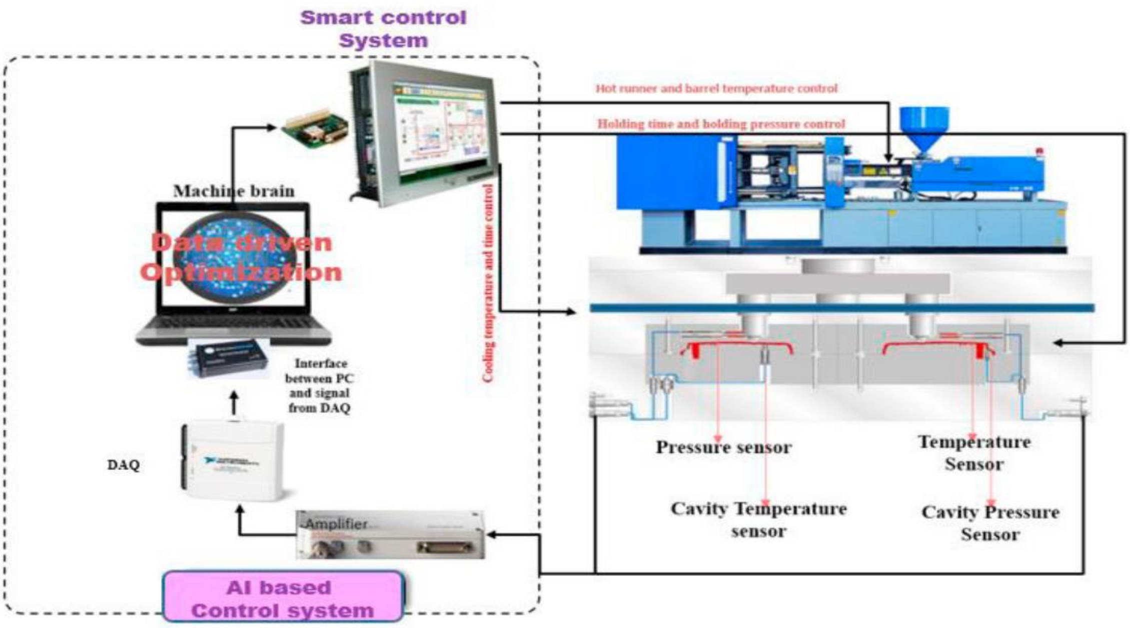


FIGURE 14: INTELLIGENT METAL INJECTION MOLDING MACHINE

7.Conclusion

Machine learning is one of the most highly actively researched and sought after topic in recent times. Deep learning is giving much better result as compared to other traditional rule based method. There are areas in Manufacturing domain where we can use Machine Learning to learn from the existing data and also ways to develop models using spared data. Currently more work is going on in the field of Manufacturing scheduling, Geometric feature recognition, Predictive maintenance, Visual inspection, inverse modelling, Logistics forecasting. There is more scope to improve accuracy of model for each case by optimizing the architecture of neural network. To summarize, deep learning algorithms and routines may present many desirable advantages and assets to solve challenges inherent to the industry of the future or industry 4.0. Also apart from benefits to large industries these techniques can be used to develop smart manufacturing machines using open source dataset and DL architecture or by developing one for small scale industries which are not actually industries but a small workshop containing one or two machines for manufacturing and supply to big assembly lines without much profit.

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