**Chapter 1**

**INTRODUCTION**

* 1. **Introduction**

Since the invention of the wheel, humans have always tried to reduce the load and burden of human effort. After the wheel was invented it opened up venues for transportation which included transporting humans, animals, food items, etc. throughout the world. This led to the discovery of gears leading to the invention of cars and automobiles. Just as the discovery of wheels started the industrial revolution, in the same way, the discovery of the “Difference Machine” by Charles Babbage [1] started the revolution in the field of using computers to automate and calculate large calculations in the field of science, mathematics, business and much more.

The concept of automation led to a curious start in the field of machine learning. “Making machines learn and do things on their own”, can be understood as a layman’s definition of machine learning. The sole focus of a machine learning system is to learn to automate the learning process [2]. Refining the algorithms and the observation that the machine learns to improve the future prediction over time.

Machine learning in itself is a concept modeled in parts, after the human brain. One of the earliest works done in this field was by Donald Hebb in 1949, in his book titled “The Organization of Behavior” [3]. After this one of the most influential works that kick-started the machine learning field was given by one of the most prominent personalities, Alan M. Turing. “Computing Machinery and Intelligence” is one of the key papers published by him in 1950, raised the question of “Can machines think?” [4].The paper argued that there isn’t any argument that can convince us that machines don’t have the ability to think like humans. The “Turing Test” designed by Alan Turing himself was the one that came up with the concept of identifying whether the answer given to a specific question is by a machine or a human being. Fig 1.1 illustrates the timeline of the evolution of the field of machine learning and artificial intelligence.

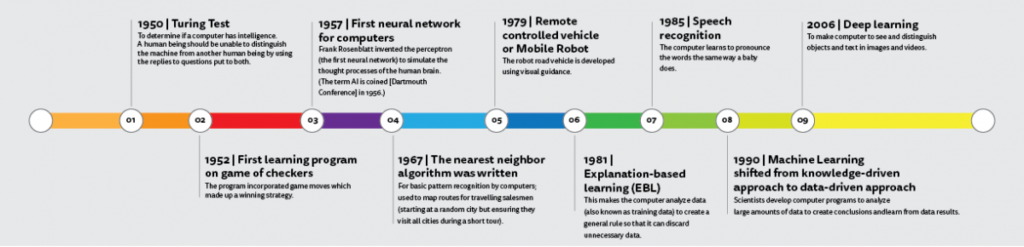


Fig 1.1 Evolution of the field of machine learning and artificial intelligence as we know it to date [5]

In the year 1952, Arthur Samuel from IBM developed a program to play checkers. In the year 1955, John McCarthy, a professor emeritus from Stanford coined the term “artificial intelligence” [6]. Keeping in conjecture to the history of the field of machine learning, in the year 1957, Frank Rosenblatt is credited with the work of the first-ever model of a computational unit modeled exactly like the brain and is best known by the name “Perceptron” [7]. The “Perceptron” can be thought of as the stepping stone for the creation of what we today know as an “Artificial Neural Network”. Moving forward in the year 1967, was the year when Cover and Hart proposed the algorithm famously known nowadays as “K-Nearest Neighbor” [8] which was then proposed to actually find the most efficient route for solving the infamous “Travelling Salesman Problem”. Moving forward in the same era, the creation of multiple layers in the area of neural networks paved a new road for research.

The creation of multiple layers led to the formation of what we today know as a “feedforward neural network”. This decade also is credited with a number of researchers coming up with the idea of one of the most important concepts in the field of deep neural networks known as “backpropagation”. Though the idea of backpropagation has been around for quite a long time, the use of backpropagation as a learning method for the neural networks can be credited to the infamous paper by Geoffrey Hinton named “Learning representation by back-propagating errors” [9]. The concept of backpropagation tells us that any artificial neural network adjusts its layers that are hidden based on reducing the value of a function which it tries to calculate by the difference between the expected and the calculated values which it terms the “error” caused due to mismatch in respective values.

Moving forward machine learning and artificial intelligence went on their separate ways with the latter generally focusing on using an approach based on logic and knowledge which is start different from what machine learning tries to do which is to draw out conclusions based on different algorithms. Machine learning started to leverage the ideas from statistics and probabilities along with concepts from artificial intelligence to solve practical problems and start leveraging for business usage.

* 1. **Literature Survey**
  2. **Problem statement of the Thesis**

The major aim of preparing this thesis is to accomplish the following goals:

1. To outline the basics in the field of machine learning and outline the different approaches in the field of machine learning.
2. To do an in-depth study of the field of deep reinforcement learning.
3. To outline the improvement that the experiment did to correct bounding boxes.
4. To provide future scope for the researcher to dive into the fascinating field of deep reinforcement learning
   1. **Organization of the Thesis**

The complete thesis is organized into multiple chapters as outlined in the following few lines:

Chapter 1: This chapter gives an overview, outlines the content, and contains the literature review that was done when working on the topic.

Chapter 2: This chapter gives a brief introduction to the field of machine learning covering various types and aspects of machine learning.

Chapter 3: This chapter will give a thorough outline of the most used neural network architecture in CNN.

Chapter 4: This chapter will outline the field of reinforcement learning and how it was used in the area of computer vision.

Chapter 5: This chapter will go into the proposed methodology and the working principle of the work that has been done during the complete tenure.

Chapter 6: This chapter will outline the total outcomes that came as a part of different experiments that were performed.

Chapter 7: This chapter will provide a conclusion and the future scope.

**Chapter 2**

**MACHINE LEARNING TECHNIQUES**

**2.1 Background**

The main problem that machine learning tries to solve is trying to find patterns in the data which act as the fundamental to that data and has a very successful past in doing so. For example, one can quote extensive works done in the field of astronomy back in the 16 century when Kepler was determined to discover some of the hidden patterns on how planets in our solar system tend to revolve around the sun. Similarly one can credit the evolvement of quantum physics at the beginning of the twentieth century to the development and discovery of atomic spectra being regular. Similarly, when it comes to the field of discovering patterns, using various computer algorithms to find out different patterns in the data to discover regularities just like Kepler or like the work done in the field of quantum physics, also after discovering the regularities in the data to help classify data in multiple categories.

Now let’s consider one of the simplest examples to outline the work done in the field of pattern recognition, the recognition of handwritten digits. One of the earliest works done in this is can be credited to Yan LeCunn in his work “Backpropagation Applied to Handwritten Zip Code Recognition” [10]. In that, each digit corresponded to 28X28 pixel images which can be converted into a vector of length that consists of 784 numbers. The main aim of this work was to develop a machine-learning algorithm to make it learn to take such vectors of length x which when fed will then produce identification in the term that which of the 10 digits that specific flattened layer of numbers belongs to. Now, this can be categorized as one of the non-trivial problems given the reason that digits can be written in different forms because of the varying handwriting of people writing them.



Fig. 2.1 Examples of handwritten digits [10]

So to circumvent the variances that might be due to different sorts of handwriting, some specific heuristics or handcrafted rules can be put in place that tend to determine what digit it can be based on the shape of strokes, but in a practical approach, it is seen that this sort of approach tends to yield bad results.

To improve the result one can use a method that uses a large collection of data commonly known as a *training dataset,* to train the machine learning algorithm by tuning the weights and learnable parameters of such model. Before training the adaptive model, the digits are already segregated based on their corresponding categories in this case every set of numbers is already known to be one of the 10 digits in a decimal number system which is done by individually marking them, in turn taking a lot of human effort. Now after the training dataset is marked there has to be something known as a *target* for the machine learning algorithm to run after, which is a *vector* giving the corresponding digits belonging to every *vector* belonging to the *training dataset.*

The complete execution of the machine learning algorithm can be defined by a function *f(x)*, where *x* can be defined as the input given to the machine learning algorithm, which generates an output *f* based on the *target* the machine learning algorithm was given. Now after the algorithm learns what it can base on the training dataset, it then tries to extend its knowledge or the weight adjustments or parameter changes it did to learn the *target*, to more unseen examples, which is known as the ability of *generalization.* In other words, it gives an indication of how a specific machine learning algorithm is able to extend its learning or *generalize* to unknown examples. As compared to all the possible combinations of inputs in the form of input vector *x*, the *training dataset* comprises a very tiny subset of all such inputs so it becomes an absolute necessity for the machine learning algorithm to have the ability to *generalize*.

When it comes to applying various machine learning algorithms in practical cases, one of the steps that are generally taken before feeding in the input to the machine learning algorithm is *pre-processing*. These are generally done to transform the hypothesis space of the input variable making it much easier for the pattern recognition systems to learn the patterns in an even better way. Pre-processing the inputs also tends to convert all of them in the same range which greatly reduces the variability of the data among themselves. Sometimes the pre-processing step taken is also known as *feature extraction.* One of the reasons to do pre-processing is to reduce the computational cost it will take for the pattern recognition algorithm to learn the differences in the input data if they are scaled to the same range.



Fig. 2.2 Different types of machine learning algorithms [11]

**2.2 Supervised Learning**

Supervised learning [12] as the name suggests is a machine learning paradigm that learns by supervision. The term *supervision* means learning with the knowledge that what is right and what is wrong based on the input you have got and based on the output you are expected to give.

The process of learning generally contains two parts, learning or training, and testing. During the process of *training*, the training dataset mentioned in the above text is given as an input from which the pre-processing step extracts the features in other words known as feature extraction [13]. When testing of the model is done, the trained and fin-tuned model uses the *testing dataset* and then predicts the expected target values [13].



Fig. 2.3 A pictorial representation of a supervised learning process [13]

A supervised learning approach uses a dataset that tends to contain a collection of features and the corresponding labels and for the testing part of the algorithm, the labels are predicted by the learning algorithm or the learner.