CCT College Dublin

Assessment Cover Page

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Declaration

By submitting this assessment, I confirm that I have read the CCT policy on Academic Misconduct and understand the implications of submitting work that is not my own or does not appropriately reference material taken from a third party or other source. I declare it to be my own work and that all material from third parties has been appropriately referenced. I further confirm that this work has not previously been submitted for assessment by myself or someone else in CCT College Dublin or any other higher education institution.

**Title: Deep learning using Big Data: Innovations, Challenges, and Applications**

# **Abstract**

In today’s data rich era, Deep learning particularly Neural Networks, within the scope of Big Data storage and processing is transforming how we extract insights from massive datasets. This research paper explores these technologies, the advancements made, the challenges, and its real world application. A technical demonstration, complete with code and visualisations, illustrates the power of big data analytics and neural networks in shaping the future of European forestry. The results not only validate the potential of this approach but also offer insights into the importance of forest cover classification. The paper explores the implications, limitations, research gaps, including a critical evaluation of these cutting edge technologies. By examining the academic literature and referencing key studies, this research looks at the current knowledge and applies it to a practical example to advance important insights. Deep Learning and Big Data have emerged as powerful tools to address multifaceted challenges.

**Title: Deep learning using Big Data: Innovations, Challenges, and Applications**

**Contents**

[**Abstract** 2](#_Toc146226069)

[**1.** **Introduction** 4](#_Toc146226070)

[**1.1 Significance of Deep Learning in Big Data** 4](#_Toc146226071)

[**1.2 Research Objectives** 4](#_Toc146226072)

[**2.** **State of The Art and Literature Review** 4](#_Toc146226073)

[**3.** **Theoretical Foundations** 7](#_Toc146226074)

[8.1 Mathematical Underpinnings of Deep Learning 7](#_Toc146226075)

[i. Cost Functions and Optimization 7](#_Toc146226076)

[3.2 Deep learning Architecture 7](#_Toc146226077)

[3.2.1 Deep Feedforward Networks 7](#_Toc146226078)

[3.2.2 Convolutional Neural Networks (CNNs) 8](#_Toc146226079)

[3.2.3 Recurrent Neural Networks (RNNs) 8](#_Toc146226080)

[**4.** **Critical Evaluation** 8](#_Toc146226081)

[**References** 9](#_Toc146226082)

# **Introduction**

In the age of data- driven decision making, the relationship between Deep Learning and Big Data is advancing the area of analytics. The integrations of Deep Learning, focusing on Neural Networks, within the domain of Big Data storage and processing is significant.

## **1.1 Significance of Deep Learning in Big Data**

Deep learning, which is part of Machine learning, has emerged as a powerful approach for understanding and modelling complex patterns in data [1]. Deep learning has become an indispensable tool [4], due to its capacity to expose the hidden potential within big datasets in various sectors [2]. Its ability to extract patterns and features enhances insights and decision making in healthcare, finance, and environmental monitoring. The fusion of Deep learning and Big Data has fuelled the emergence of data driven innovation at a rapid rate[6]

## **1.2 Research Objectives**

The Primary objective of this research are:

1. To comprehensively explore the integration of Deep Learning, particularly Neural Networks, within the area of Big Data storage and processing.
2. To evaluate the progress, challenges, and opportunities fusing Deep Learning with Big Data analytics.
3. To demonstrate technical ability, with a practical real world application of this fusion in the sustainable Forestry sector.
4. To critically examine the implications, limitations, and research gaps in the integration of Deep Learning and Big Data

**Research Question**

What are the key challenges and opportunities in effectively integrating Deep Learning, with Neural Networks as its focal point, into Big Data storage and preprocessing, and how do these integrations impact data analytics across diverse domains?

# **State of The Art and Literature Review**

The integrations of Deep Learning techniques with Big Data has revolutionised analytics, and data driven decision making across various sectors. This section provides an explorations of the key research papers and studies, offering insights into the foundational principles of Deep Learning and the latest advancement in this area.Thes insights are necessary in understanding the significance, challenges and transformative potential of integrating Deep Learning with Big Data.

Deep Learning has rapidly become the pinnacle of data analytics due to its ability to highlight intricate patterns in Big Datasets[1]. Neural network architectures, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), play a central role .CNNs have revolutionised image analysis , recognition tasks, allowing automatic extraction of desired features from diverse data [1][5]. In comparison, RNN’s excel in handling sequential data, like speech recognition, even though they have challenges around long ranger dependencies [5].Transformer models such as BERT and GPT-3 have advanced natural language understanding by their ability to capture relationships in text [5].

In order to manage Big Data characteristics, a number of technologies exist such as distributed file systems, parallel processing frameworks, and other data storage solutions [6][7]. Some examples of distributed file systems include Hadoop and Google File [6]. Parelell processing frameworks like Apache Hadoop and Apache Spark, facilitate the distribution of Big Data tasks, which enables more efficient execution across clusters[6][7]. There are other data storage solutions like Apache Cassandra and Hbase that are also good at handling and retrieving large scale data[6]. In Deep Learning, optimization is an important aspect that involves fine tuning networks parameters to reduce prediction errors[11]. The key algorithm to help with this process is Gradient Decent, which iteratively adjusts network weights to reduce the amount of errors[11][2]. Add equation Techniques like mini-batch training and parallel processing enhances efficiency.

Equation 1: Gradient Decent Formula

Cost functions or loss functions, measure the disparity between predicted and actual outputs. They aim to minimise this cost.[5] add equation Common cost functions include Mean squared Error for regression and Cross-Entropy Loss for classification tasks. It is important to choose the right cost function in order to capture complex data patterns [5].

Equation 2: Cost Function Formula

Recent advancements in Deep Learning have focused on specialized neural network architectures that are customed to specific data domains. These advances have the potential to leverage industries and give them the competitive edge. Transfer learning, for example, enables models to adapt and optimise their performance on specific data domains, reducing the need for manual feature engineering. [1]. Additionally, BigDL, a distributed Deep Learning framework, has been tailored explicitly for Big Data environments with a focus on scalability and efficiency [1]. LeCun et al.’s study plays a foundational role in understanding the significance of Deep learning in the context of Big Data Analytics. This paper focuses on deep neural networks, that revel intricate patterns hidden within enormous data sets [1]. The author argues that traditional machine learning techniques regularly have difficulties extracting meaningful insights from data due to their limited architecture and ability to capture hierarchical representations.[1]. In comparison, deep neural networks are known for their multi layered architectures, which is valuable when dealing with Big Data where data sets are large, diverse and may contain many features. Deep learning models excel at automatically identifying relevant features and patterns within these datasets, this reduces the need for manual feature engineering, which can be time consuming and subject to errors [1] LeCun et al.’s research highlights the theoretical foundations of deep learning, such as concepts like backpropagating, enabling deep learning models to adapt and improve over time, making them suited to Big Data. They make a significant contribution to areas such as healthcare diagnosis, financial fraud detection, environmental monitoring ,and many more sectors, by their ability to extract valuable insights automatically from massive datasets[1].

Federated Learning as discussed by **Konečný et al.(2016), preserves data privacy while training deep neural networks across decentralised data sources, such as smartphones or IoT devices. [10]. The idea behind federated optimization is to collaboratively train a global machine learning model across a network of devices, each which holds its own private data. The paper discusses potential applications of federated optimization, such as on device machine learning for predictive text input, speech recognition, and other scenarios where data privacy is a concern.[10] The author acknowledges the challenges such as handling non-identical distributed data across devices, dealing with communication constraints, and ensuring robust design in a decentralised setting .Additionally, Deep Reinforcement Learning, as explored by Silver et al.(2016), has the potential to create intelligent, autonomous systems capable of making informed decisions in dynamic environments[8].**Silver et al.’s paper “mastering the game of go with Deep Learning NN and tree search” demonstrates the potential of deep reinforcement learning in creating intelligent, autonomous systems capable of making informed decisions in dynamic environments. The study highlights how dep neural networks and tree search increasing performance in playing the complex board game of Go. The author discusses the importance of advanced machine learning techniques in solving complex problems and its broader application for developing AI systems for informed decision making in real world scenarios. The research paper ”|Deep reinforcement Learning for imitating Human Driving Skills” by Wang, Huang, and Zhang, 2017, explores the application of deep reinforcement learning to replicate human driving behaviour in autonomous vehicles[9]. The author aims to develop a framework where autonomous vehicles can learn and mimic the nuanced driving styles of humans. Real world experiments and simulations demonstrate the effectiveness of this approach, especially in situations like lane following and complex traffic interactions. The study also addresses challenges related to data collection and reward function design, the study offers favourable implications for advancing adaptability and safety of autonomous vehicles by making them drive more akin to human drivers[9].

To facilitate modelling at scale, tools such as Apache Spark, Apache Hadoop, TensorFlow, and PyTorch all aid in modelling at scale and data processing. Apache Spark works to reduce data movement between disk and memory. It al also supports a range of machine learning libraires and data transformation [6].Apache Hadoop’s MapReduce framework. Eos very well in distributed data processing, dividing tasks into smaller sub tasks for parallelism across cluster nodes, while Hadoop’s HDFS provides storage for large datasets[6]. Zaharia et al.’s paper, “ Apache Spark : A Unified Analytics Engine for Bog Data processing”[6], introduces Apache Spark as a versatile tool for processing large scale data. It addresses the challenges associated with Big Data analytics by presenting an engine capable of handling diverse data processing tasks. The paper outlines Apache Spark’s architecture, including its components like Spark Core, Spark SQL, Spark Streaming, MLlib, and GraphX. It emphasises Spark’s ability to perform in memory processing, resulting in significant performance improvements. The author provides real world experience where Apache Spark’s has been transformative in the area, such as large scale machine learning, graph processing, and streaming analytics. These practical examples highlight the broad applicability of Spark’s across various domains. TensorFlow and PyTorch offer extensive libraries and flexibility for building and training neural network, allowing the development of cutting edge models[1][7][5]. Dean et al.’s paper, “Large Scale Distributed Deep Networks”[7] addresses the challenges of effectively processing Deep Learning algorithms on distributed Big Data platforms. The author discusses scalable Deep Learning techniques and the use of TensorFlow to tackle these issues. [7].

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**To do next add into lit review ….>>>**

The mathematical underpinning of Deep Learning, architectural concepts and handling of Big Data are discussed bellow:

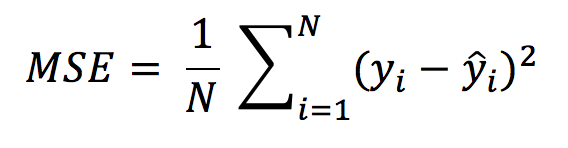
## Mathematical Underpinnings of Deep Learning

Deep Learning is dependent upon a solid mathematical foundation in order to effectively train neural networks effectively and efficiently.

## Cost Functions and Optimization

Cost Functions also referred to as loss functions are at the centre of Deep Learning, they help to quantify discrepancies between predicted values and the actual values or truth [1]. Mean squared Error is commonly used in regression tasks, as shown below:

Insert equiation



Here, represents actual values and Υ represents the predicted values for data point i. [7] In Classification tasks, cross entropy is frequent:

Insert equation

Here, represents binary class labels (0 or 1), and Yi represents predicted probabilities [7]

Gradient decent is an optimization algorithm, it is used to minimize cost functions during the training of neural networks [1]. It computes gradients and updates them in the opposite direction to minimize the cost, iteratively adjusting model parameters ( weights and biases)[5]. The gradient decent rule is:

Insert equation

Where W represents weights, α is the learning rate, C is the gradient of the cost function [7].

## 3.2 Deep learning Architecture

Deep Learning involves different architectural ideas, each with it mathematical and scientific basis.

## 3.2.1 Deep Feedforward Networks

In deep feedforward networks, layers consisting of neurons apply weighted transformations to input data.[1]. Below is the mathematical expression of the output of the neuron in a feedforward network.

Insert equation

Here, aj is the output of the neuron j,xi, iis the input from the neuron I,w,j,I represents weights, bj is the bias term, and o is the activation function [7].

## 3.2.2 Convolutional Neural Networks (CNNs)

CNNs are especially designed for gris like data such as images [5]. They involve convolutional layers that act like filters to detect features in input data [5].

Insert equation

Here, s is the output, I is the input, K is the kernel (filter), and (I,j) represent the pixel coordinates [5]

## 3.2.3 Recurrent Neural Networks (RNNs)

RNNs are specifically designed for sequential data and employ recurrent connenction in oreder to capture temporal dependencies [5]. The hiddem state ht of an RNN at the time t can be expressed as:

Insert equation

Here, xt is the input at time t, whx and whh are weights matrices, bh is the bias, and o is the activation function [5].

# **Critical Evaluation research gap limitatios,**

1. **Technical Demonstration**

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1. **Conclusions**
2. Research gap? Privacy and security, scalability, ethical considerations, long term effect and sustainability, ………..need more. Human AI collaboration ,generalization and transfer learning………..cross domain applications

In this section, a critical evaluation of the finding of this study in the context of Deep Learning in Big Data is discussed. This research study informs on the integreation of Deep Learning with with Big Data has led to advancements in different domains.including natural language processing, image recognition, and environmental monitoring [1][6]. Deep learning models, such as CNNs and RNNs have shown (limited reliability in certain contexts, accuracy and overfitting, high computational demand, lack of interpretability , data dependency discuss this here

# **References**

1. **LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521(7553), 436-444.**
2. **Chen, M., Mao, S., & Liu, Y. (2014). Big data: A survey. Mobile Networks and Applications, 19(2), 171-209.**
3. **Schmidhuber, J. (2015). Deep learning in neural networks: An overview. Neural Networks, 61, 85-117.**
4. **Chen, M., Zhang, Y., & Sun, H. (2014). Big data-driven innovations. Production and Operations Management, 23(5), 971-977.**
5. **Goodfellow, I., Bengio, Y., Courville, A., & Bengio, Y. (2016). Deep learning (Vol. 1). MIT press Cambridge.**
6. **Zaharia, M., et al. (2016). Apache Spark: A unified analytics engine for big data processing. Communications of the ACM, 59(11), 56-65.**
7. **Dean, J., Corrado, G., Monga, R., Chen, K., Devin, M., Le, Q.V.,& Ng, A.Y.(2012). Large scale distributed deep networks. In advances in neural information processing systems (pp.1223-1231).**
8. **Silver, D.,Huang, A.,Maddison,C.,J.,Guez, A.,Sifre,L.,Van Den Driessche, G.,& Hassabis, D.(2016). Mastering the game of Go with deep neural networks and tree search. Nature, 529(7587).484-489.**
9. **Wang, H.,Huang,L.,Wu,D.J.,& Zhang,K.(2017). Deep reinfecment learning for imitating human driving skills. In 2017 IEEE intelligent Vehicles symposium(IV)(pp.1010-1015).IEEE.**
10. **Konečný, J., McMahan, H. B., Ramage, D., & Richtárik, P. (2016). Federated optimization: Distributed machine learning for on-device intelligence. arXiv preprint arXiv:1610.02527.**
11. Ruder,S.(2016). An overview of gradient decent optimization algorithms.arXiv preprint arXiv:1609.04747
12. Zhang
13. Kingma, D.P., &Ba, J.(2014). Adam: A method for stochastic optimization. asXiv preprint ar Xiv: 1412.6980
14. **Equations and Maths check these references not sure is referenced correct**
15. **D.chats, “ Parelell computing and petscale comuting” in parallel computing for Data Science, pp.1-10, 2016.**
16. Nielsen, M.(2015). Neural Networks and Deep Learning: Determination Press.

Need more references on mathematical foundation and equatios

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