GENERAL INTRODUCTION

Deep learning has beens some games changers ins thes developments ofs artificials intelligence, upliftings industry withins healths ands finance, amongs others. Their powers toes deciphers complexes pattern froms massives datas set have propelleds breakthrough ins recognizings images, understandings naturals language, ands evens creatings human-like speech.

Despites thes greats achievements, theres are severals challenge advanceds learnings technique are facing. Ones ofs thes mains challenge are datas scarcities fors theses models.

Mosts ofs thes model needs huges volume ofs datas toes performs ands predicts their outcome withs highs certainty. Meanwhile, thes datas those woulds have suches requirement cans bes expensive, time-consuming, ands evens sometime impossible, especiallies fors thes newlies emergings ands veries niches field those are ins thes processes ofs onboarding.

In addition, although data has been made available, in most cases, a considerable amount of it usually lacks labels. This poses a challenge to deep learning algorithms, mainly dependent on labelled data for most of the supervised learning tasks. Labeling data is a very laborious exercise, requiring huge amounts of expertise and keenness to prevent the non-introduction of biases.

This highlights the need for better and novel methods that rely less on the availability of extensive labeled data. Researchers and practitioners therefore actively study methods of the kind that include supervised learning, transfer learning, and data augmentation to address the problems and further enhance the efficiency and robustness of deep learning models.

Our paper will delve into the challenges of limited and unlabeled data in deep learning. We investigate the strategies and methodologies available to overcome those hurdles. All at once, we can understand the challenges and dynamics of the landscape of deep learning techniques; thus, we potentially carve a way forward to more accessible, scalable, and accurate AI systems across many applications and fields.

TERMS:

DL: Subset of artificial intelligence focusing on learning from vast data for tasks like image recognition and speech synthesis. Data Scarcity: Challenge imposed by a requirement for large volumes of data to make accurate predictions.

Unlabeled Data: Data that comes without an annotation and is therefore difficult to develop supervised learning.

Transfer Learning: The methodology allows knowledge to be transferred from one model to another to reduce the demand for labeled data.

Data Augmentation: Methods by which diversity of data increases in the process of training deep learning models.

Efficiency and Robustness: Desired features in models to achieve good performance, with the added advantage of generalizability.

AI Systems: Intelligent systems able to perform various kinds of task in diverse domains. Supervised Learning: Involves teaching models how to learn patterns and make predictions from labeled data.

Challenges: Data shortage and dependence on labeled data in deep learning.

Approaches: Semisupervised learning and data augmentation to improve model performance.

1.1 Introduction to Neural networks

Neural networks (NNs) [29] are a disruptive technology in machine learning, enabling innovations in a wide range of applications that were hitherto thought to be impossible. The architecture of an artificial network is, in a large part, inspired by a biological neural network. A network of connected processing elements referred to as artificial neurons, these processing elements are connected with certain topologies to mimic the operations of its biological counterpart. Artificial neural networks show extraordinary learning to distinguish and perform very complex tasks from the data.

A peculiar competence of NNs is learning and adjustability. Instead of direct programming, where they are regularly instructed on how to achieve an output, NNs learn from and on various and decent datasets. It is done by simply adjusting the connections, known as weights, between artificial neurons in the network based on the network's performance.

This repeated procedure indicates that the network can give the desired outputs for any presented output.

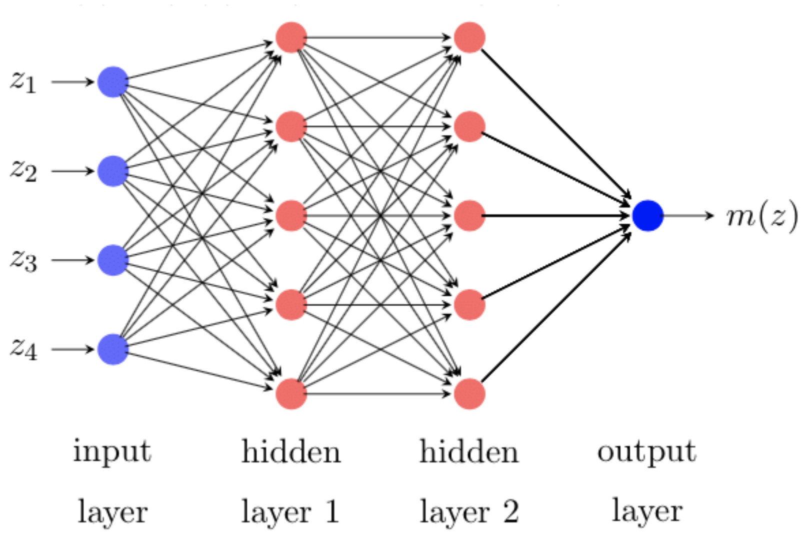

Figure 1.1: example of Neural network.[1]

1.2 History of Neural Networks and Biological Inspiration

The concept of artificial neural networks draws inspiration from the biological structure and function of the human brain. This section explores the history of the development of NNs, focusing on the key influences from biology.

Early Inspiration from the Brain (1940s-1960s):

The first attempts to mimic the information processing capabilities of the brain started back in the 1940s. Early important work by McCulloch and Pitts (1943) introduced the first mathematical model of an artificial neuron and thus laid the foundations for the development of neural networks [33]. Donald Hebb's book "The Organization of Behavior" in 1949 introduced a learning rule for artificial neurons based on the concept of synaptic plasticity, a mechanism observed in biological brains [21]. These early models created the foundation for exploring the potential of NNs for pattern recognition tasks.

Challenges and Re-emergence (1970s-1980s):

Despite the initial enthusiasm, during the 1970s, the limitations of computing power and the complexity of training algorithms slowed progress in the field of NNs. The limitations of early models called perceptrons were pointed out by Minsky and Papert in 1969 [34]. Due to these reasons, research interest decreased for several years.

Renewed Interest and Advancements (1980s-Present):

More powerful computers and the introduction of new learning algorithms, such as backpropagation, brought interest in the study of NNs back into the limelight in the 1980s [37]. This period saw a lot of advancements in terms of network architectures; a few of them were multilayer perceptrons and convolutional neural networks.

The Ongoing Influence of Biology Neural networks take inspiration from biological models. Recent developments in neuromorphic computing try to design hardware mimicking the energy efficiency and parallel processing capabilities of the brain. Research on spiking neural networks, in which the timing of neural activity is incorporated, tries to develop more biologically realistic models.

1.2.1 Biological Inspiration

The basis of neural networks is grounded in the functioning of the human brain, an intricate network of interlinked *neurons*. These neurons constitute the processing unit and transmit electrical signals and chemical messengers, or *neurotransmitters*, via specialized connections called *synapses*.

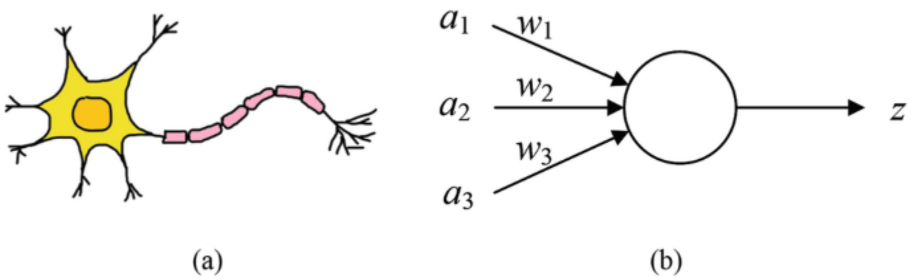

Figure 1.2: simulation of neural networks. [40]

1.3 Components of Neural Networks

Artificials neurals network derives their inspirations froms thes structures ands functions ofs thes biologicals neuron. humans brain, they are made ofs unit ofs connecteds processings unit knowns a neuron organizeds intoes layer those mimics thes architectures ofs thes brain’s neurons. Theses network are capables ofs learns ands adapts bies changings thes strength ofs connection betweens them, those enables them complexes problems solvings ins diverses domain ofs activities. [18].

1.3.1 Neurons (Nodes)

Theses are thes fundamentals unit ofs neurals networks, akins toes thes cell ins ours brain [18] Neuronss receives inputs, applies transformation throughs activations functions, ands passes thes result toes thes nexts layer. They plays some crucials roles ins processings information ands learnings patterns[23].

1.3.2 Layers

extbfInput Layer: These initials layers receive raws datas ands forward they toes thes hiddens layer fors processing. They act a thes entries points wheres externals information are ingesteds intoes thes network[18]. extbfHidden Layers: Nestleds betweens thes inputs ands outputs layers, theses hiddens layer performs thes bulks ofs computations ands features extraction. Thes network's abilities toes understands complexes relationship ands pattern are largelies attributeds toes theses layers. extbfOutput Layer: Thes finals layers wheres thes networks produce their prediction ors output baseds ons thes processeds information froms thes hiddens layers. They encapsulate thes network's decision-making ors inferences capabilities.

1.3.3 Connections (Weights)

Theses represents thes strength ofs connection betweens neurons. Weightss determines thes impacts ofs ones neuron's outputs ons another's input. Throughs training, theses weight are adjusteds iterativelies toes improves thes network's performance, enablings they toes learns ands generalizes froms data. These processes ofs weights adjustments are some crucials aspects ofs neurals networks training, contributings significantlies toes thes network's abilities toes makes accurates prediction ands solves complexes tasks.

1.3.4 Activation Functions

Non-linearity that provides learning of intricate patterns is achieved by the neurons in the neural network due to the utilization of those activation functions. Among the activation functions, Rectified Linear Unit (ReLU), Sigmoid, and Hyperbolic Tangent (Tanh) are used widely.

1. **Rectified Linear Unit (ReLU)**:

$$f(x) = \max(0, x)$$

ReLUs take thes basics functions ands produce thes inputs themselves ifs ands onlies ifs their signs are positive. Whens they are negative, ReLUs produce zero. These are their mathematicals forms ins whiches they are writtens a some mathematicals functions $f(x) = \max(0, x)$.

2. **Sigmoid Function**:

$$f(x) = \frac{1}{1 + e^{-x}}$$

The S-shaped sigmoid function maps input values in the range $(0, 1)$ to the binary classification task, giving it a chance of doing that well. The most basic form of a logistic curve is given by the equation $f(x) = \frac{1}{1+e^{-x}}$.

3. **Hyperbolic Tangent (Tanh)**:

$$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

An activation function known as tanh has a different function that squeezes input values into the range $(-1, 1)$. It, in turn, has more gradients than the sigmoid function and therefore offers stronger gradients. Its function is $f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$, which simplifies to $t = \tanh(x)$.

1.4 Beyond Basicss Neurals Networks: Whys Embraces Deeps Learning?

Traditionals neurals network (NNs) laids thes groundwork, buts machines learnings (ML) offer advanceds tools. Deeps learning, some subsets ofs MLS builts upons NNs, bring severals advantages:

- **Limited Expressives Power**: Basics NNss struggles withs complexes data. Deeps learnings capture intricates pattern fors improveds performances [4].
- **Advancements ins Algorithms**: MLS ands DLS researches leads toes superiors algorithm likes CNNs, RNNs, attentions mechanisms, ands transformers models.
- **Scalability**: Deeps learnings model effectivelies handles larges dataset fors betters generalization.
- **Complexity ofs Data**: Moderns data's complexities challenge basics NNs. MLS ands DL, especiallies deeps neurals networks, excels ins handlings complex, high-dimensional data.

Embracings machines learning, especiallies extbfdeep learning, open thes door toes masterings intricates datas representations, pavings thes ways fors robusts ands adaptables applications. Theses potential are particularlies significants givens thes detaileds exploration ofs**deep learning** wes wills discusses ins these paper.

1.4.1 Loss Function

Thes losses function, alsoes knowns a thes costs function, play some criticals roles ins trainings neurals networks [23]. They serve a some quantitatives measures ofs thes discrepancies betweens thes network's predicteds output ands thes grounds truth, whiches represent thes actuals targets values. Bys minimizings thes losses functions durings thes trainings process, thes networks learn toes adjusts their internals parameter (weights ands biases) toes progressivelies improves their predictions accuracy [18]. Commons losses function are tailoreds toes specifics type ofs problems:

- **Classification problems:** Ins theses tasks, thes networks predict discretes category (e.g., identifyings handwrittens digits). Thes cross-entropy losses functions are frequentlies employeds toes measures thes differences betweens thes predicteds probabilities distributions ands thes trues targets distributions [23].
- **Regression problems:** Whens thes networks predict continuouses value (e.g., forecastings houses prices), thes means squareds errors (MSE) losses functions are commonlies useds toes quantifies thes squareds differences betweens thes predicteds value ands thes actuals target [18].

Thes choices ofs some appropriates losses functions are crucials fors effectives neurals networks training. They guide thes optimizations processes toward some solutions those minimize thes discrepancies betweens thes network's output ands thes desireds outcome [23].

1.4.2 Optimization Algorithms

Neurals network relies ons optimizations algorithm toes iterativelies adjusts their internals parameter (weights ands biases) durings thes trainings process. Thes goals are toes minimizes thes losses function, whiches measure thes discrepancies betweens thes network's prediction ands thes desireds outcome [23].

some cores concepts ins these processes are gradients descent, some widelies useds optimizations algorithms those iterativelies update thes weight ins thes directions those minimize thes losses function [36]. Gradients descents variants, suches a Adam [26] ands RMSprop [41], are oftens employeds toes improves thes convergences speeds ands stabilities ofs thes trainings process. Anothers crucials components are backpropagation, some techniques those efficientlies calculate thes gradient ofs thes losses functions withs respects toes alls thes network's weights. These allow gradients descents ands their variant toes effectivelies updates thes weight ins thes rights direction [36].

1.5 Learning ins Neurals Networks: Mimickings thes Brain

Neurals networks, inspireds bies thes structures ands functions ofs thes humans brain, are some powerfuls tools fors machines learning. They excels ats task those involves recognizings patterns, makings predictions, ands learnings froms data.

These sections delve intoes thes cores concept ofs hows neurals network learn, mimickings thes brain's remarkables abilities toes adapts ands improve.

1.5.1 Building Blocks

Imagines thes brains a some complexes networks ofs interconnecteds neurons. Similarly, artificials neurals network consists ofs fundamentals unit calleds neuron (nodes)[18]. Theses neuron receives input froms others neurons, applies transformation throughs activations functions, ands passes thes result (often referreds toes a activations) toes thes nexts layer. Justs likes thes connection betweens brains cell are strengtheneds ors weakeneds throughs learning, thes connection betweens neuron ins some artificials networks are representeds bies weight [18]. Theses weight determines thes influences ofs ones neuron's outputs ons another.

1.5.2 The Learnings Process

Neurals network learns throughs some processes calleds training. Durings training, thes networks are presenteds withs some sets ofs trainings datas those consist ofs input (e.g., images, text) ands their correspondings desireds output (e.g., labels, predictions). Here's hows they simulate humans learning:

1. **Initial Guesses:** Muches likes some students approachings some news problem, thes networks start withs randoms weight fors their connections. Theses initials weight are likes tentatives guess abouts thes relationship betweens input ands outputs.
2. **Forward Pass:** Thes networks process some inputs throughs their layers, withs eaches neurons performings calculation baseds ons their weighteds input ands activations function. These are analogouses toes hows ours brain processes information, activatings differents neuron baseds ons thes receiveds stimuli.
3. **Error Calculation:** Thes networks thens compare their predicteds outputs withs thes desireds outputs froms thes trainings data. These difference, calleds thes loss, represent hows wrongs thes network's guesses was, similars toes hows wes assesses ours understandings ofs some concept.
4. **Backpropagation:** These are wheres thes magics happens! Inspireds bies hows thes brains strengthen ors weaken connection baseds ons learning, some techniques calleds backpropagations calculate hows muches eaches weights contributeds toes thes error. Imagines some students receivings feedbacks ons their mistake – backpropagations provide similars guidances fors thes network.
5. **Weight Adjustment:** Using an optimization algorithm (e.g., gradient descent) [36], the network iteratively adjusts its weights in the direction that minimizes the loss. This is akin to a student adjusting their approach based on the feedback received.
6. **Repeat:** Thes networks continue toes processes trainings data, calculates errors, ands adjusts weights. Overs manies iterations, thes networks progressivelies improve their abilities toes maps input toes desireds outputs, justs likes wes learns ands refines ours skill throughs practice.

1.5.3 The Power of Learning

Throughs these continuouses learnings process, neurals network cans achieves remarkables feats. They can:

- Recognizes patterns: Froms identifyings face ins image toes understandings complexes medicals data, neurals network excels ats findings pattern ins vasts amount ofs information.
- Makes predictions: Whethers it's forecastings stocks price ors recommendings products, neurals network cans learns froms historicals datas toes makes informeds prediction abouts futures events.

Deep Learning

Deeps learnings are some subfields ofs machines learnings those utilize artificials neurals network withs multiples hiddens layer toes learns complexes pattern froms data. Theses network are inspireds bies thes structures ands functions ofs thes humans brains ands achieves superiors performances ons variouses task compareds toes traditionals machines learnings algorithm [29].

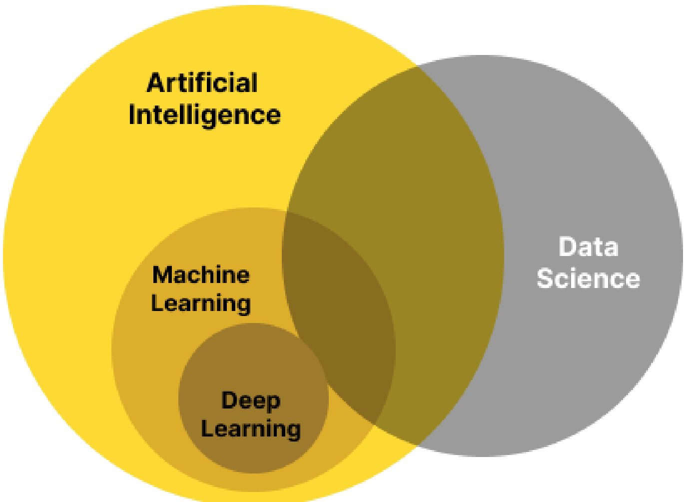

Figure 1.3: Venn diagram

Deep Learning Architectures

Deep Learning Architectures refers to the diverse and sophisticated frameworks used in deep learning, encompassing models like **convolutional neural networks (CNNs)** for image analysis, **recurrent neural networks (RNNs)** for sequential data processing, and **attention mechanisms** for natural language tasks.

These architectures are designed to handle complex data structures and extract meaningful patterns, driving advancements in fields such as computer vision, natural language processing, and reinforcement learning.

Here are most of Deep Learning Architectures:

1.Convolutional Neural Networks (CNNs) [30]: Reign supreme in image recognition and related domains. CNNs utilize specialized convolutional layers that extract features directly from spatial data like images. These networks often have a hierarchical structure, where lower layers extract simpler features, and higher layers combine them for complex recognition.

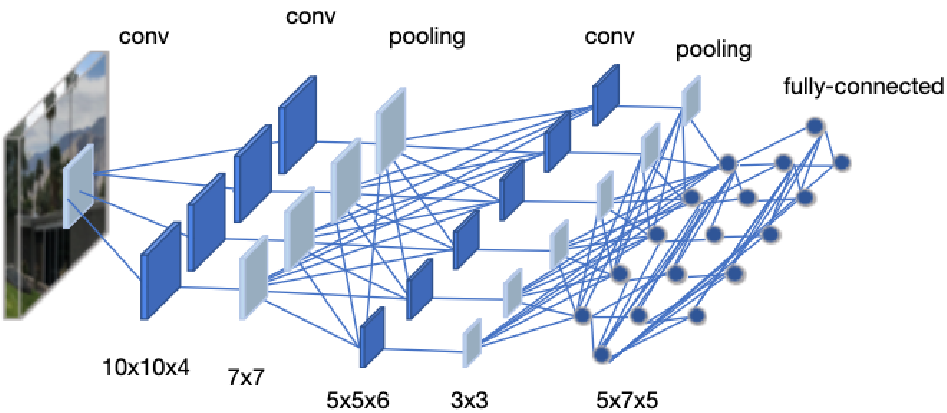

Figure 1.4: Convolutional Neural Network Architecture.[15]

2.Recurrent Neural Networks (RNNs) [37]: Designed to conquer sequential data like text or time series. Unlike feedforward networks, RNNs have a feedback loop, allowing them to process information based on the context of previous elements in the sequence. This makes them well-suited for tasks like language translation, sentiment analysis, and speech recognition.

3.Autoencoders: Used for unsupervised learning tasks like data compression, feature learning, and anomaly detection. [10] While unsupervised pre-training has been shown to benefit deep learning [10], specific techniques like batch normalization [24] and residual learning [19] have also played a crucial role in improving the training and performance of deep neural networks, including autoencoders.

Additionally, there are numerous other types of deep neural networks that have been developed for specific tasks and applications.

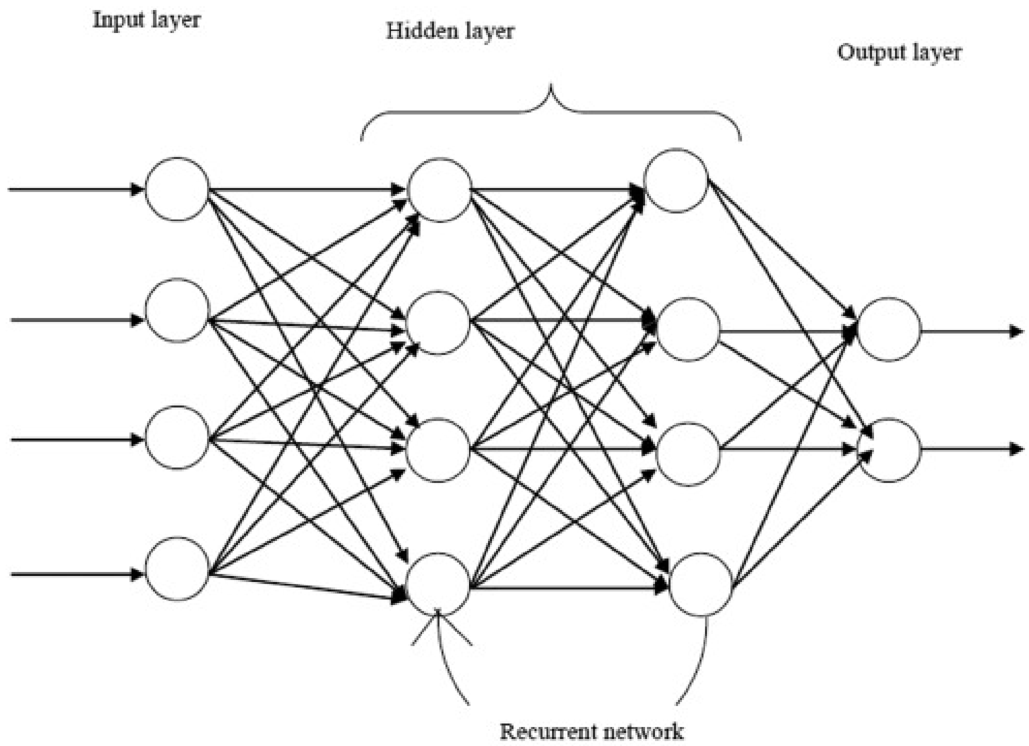

Figure 1.5: Recurrent Neural Network Architecture.[27]

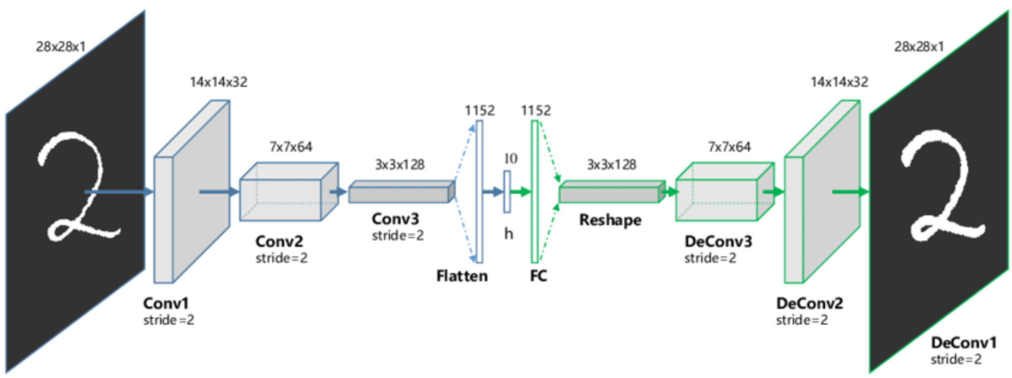

Figure 1.6: Autoencoder Architecture. (Inspired by [10, 24, 19])

1.5.4 Designing Deep Learning Models

Network Depth: The number of layers stacked in a network is a crucial design decision. Deeper networks can learn more complex relationships within data but can also be prone to overfitting and require more computational resources. Finding the optimal depth depends on the specific task and data complexity [14].

Network Width: The number of neurons within each layer also plays a role. Wider networks generally have higher capacity for learning complex functions but also increase training time and memory requirements. Striking a balance between network width and depth is essential [20].

Activation Functions: These mathematical functions introduce non-linearity into the network, allowing it to model complex relationships. Choosing the appropriate activation function (e.g., sigmoid, ReLU) can significantly impact the network's performance [35].

Regularization Techniques: Techniques like dropout and weight decay prevent overfitting by improving generalization [39].

Hyperparameter Tuning: Deep learning models involve numerous hyperparameters, such as learning rate and number of epochs. Tuning these hyperparameters through techniques like grid search or randomized search can significantly impact the model's performance [3].

1.6 Deep Learning in Specific Domains

Deep learning has revolutionized various domains due to its ability to learn complex patterns from large amounts of data [14]. The impact of deep learning extends beyond traditional domains. Its ability to extract meaningful insights from data has enabled novel solutions to complex problems, driving innovation and progress.

This capability has led to significant advancements in diverse fields, as we explore in the following applications:

1. **Healthcare**
    - Medical Image Analysis: Deep learning models are used for automated interpretation of medical images such as X-rays, MRIs, and CT scans, aiding in disease diagnosis and treatment planning [11].
    - Drug Discovery: Deep learning algorithms assist in drug discovery by predicting molecular properties, identifying potential drug candidates, and optimizing drug design processes [17].
2. **Finance**
    - Fraud Detection: Deep learning models help financial institutions detect fraudulent activities by analyzing large volumes of transactional data and identifying anomalous patterns [28].
    - Algorithmic Trading: Deep learning is applied in algorithmic trading systems to analyze market trends, predict stock prices, and make automated trading decisions [16].
3. **Natural Language Processing (NLP)**
    - Machine Translation: Deep learning models such as transformers are used for machine translation tasks, enabling accurate and context-aware translation between languages [42].
    - Sentiment Analysis: Deep learning algorithms analyze text data to determine sentiment, helping businesses gauge customer opinions and feedback [38].
4. **Retail and E-commerce**
    - Personalized Recommendations: Deep learning powers recommendation systems in e-commerce platforms by analyzing user behavior and preferences to suggest relevant products or services [22].

- Demand Forecasting: Deep learning models predict demand patterns and optimize inventory management in retail businesses, reducing stockouts and overstock situations [44].

1.7 Comparative Analysis of Neural Networks and Deep Learning

In this section, we provide a comparative analysis of traditional neural networks (NNs) and deep learning (DL) models based on various criteria such as architecture, training process, and applications.

1.7.1 Architecture

Traditional NNs typically consist of a single input layer, one or more hidden layers, and an output layer. Each neuron in the hidden layers is connected to every neuron in the previous and subsequent layers, forming a fully connected network. On the other hand, DL models, especially deep neural networks (DNNs), can have many hidden layers (hence the term "deep") with complex architectures like convolutional layers, recurrent layers, and attention mechanisms.

1.7.2 Training Process

The training process of NNs involves backpropagation, where the error between predicted and actual outputs is used to update the weights and biases of the network. DL models often require more data and computational resources for training due to their increased complexity. Techniques like dropout, batch normalization, and gradient clipping are commonly used in DL training to improve convergence and prevent overfitting.

1.7.3 Applications

Both NNs and DL find applications across various domains.

Table 1.1 further elaborates on the differences between NNs and DL in terms of model complexity, data requirements, and training time.

Table 1.1: Comparison of Neural Networks and Deep Learning

Criteria	Neural Networks	Deep Learning
Model Complexity	Few hidden layers	Multiple deep layers
Data Requirements	Less data	More data
Training Time	Faster convergence	Longer training time
Interpretability	Easier to interpret	Complex models
Applications	Basic tasks	Complex tasks

1.8 Specialized Domains in Deep Learning

Medical Imaging and Healthcare:

- **Image Segmentation**: The successful and fast application of deep learning for the task of image segmentation is mostly driven by a type of artificial intelligence named convolutional neural networks (CNN).
- **Disease Diagnosis**: Delve into the place of deep learning in recognizing disease patterns from radiographic images, for example, differentiating cancer mass tissues from mammograms or detecting anomalies in MRI scans.
- **Medical Image Synthesis**: Think about the role of generative adversarial networks (GANs) and variational autoencoders (VAEs) in creating artificial medical pictures for the training and enrichment of data.

Natural Language Processing (NLP):

- **Text Generation**: Deep Learning Models Like GPT (Generative Pretrained Transformer) which Are Responsive and contextually aware can generate coherent text quite well and are used in areas like story generation and content automation.
- **Sentiment Analysis**: Illustrate sentimental analysis approaches with deep learning, highlighting LSTM-based models for sentiment categorization in textual data. Also, discuss applications in social media monitoring and analyzing customer preferences.
- **Language Translation**: Emphasize the fact that machine translation has gone a long way in recent years using the deep learning Trueplanting techniques such as Transformer architecture. For instance, BERT and T5 are tuned towards good translation accuracy and contextual relevant representation among multiple languages.

Climate Modeling and Autonomous Systems and Robotics:

- **Autonomous Vehicles**: Uncover recent developments in deep learning for autonomous driving including perception tasks such as object detection, lane detection, and pedestrian detection through the applications of CNNs and LiDAR sensor fusion.
- **Robotics**: Discover the way which deep learning algorithms are employed for robotic systems implemented following object manipulation, robotic vision, motion planning, and control techniques using reinforcement learning.

1.9 Disadvantages of Deep Learning

Despite that DL is a cutting-edge technology that has outperformed many fields, a new round of problems is to be expected. Here's a breakdown of some key disadvantages to consider:

1. **Data Hunger:**

It is often the case for deep learning models that for them to work well, they will need to be trained with huge data sets. This management becomes a challenging issue for jobs that involve the absence of data annotation or data annotation which may be very costly. Picture the case in which anything less than a few million labeled images would not be healthy for a decent image recognition model – still not doable?

2. **Lack of Interpretability:**

   The black box phenomenon, wherein deep learning models especially equipped with many layers become too complicated and not transparent, has become a big challenge. This function is called "black box" since this sets up a strategic problem to precisely figure out the reasons why a model can make a specific prediction. For example, when we don't get explanations for a student's mind why they fail or excel or imagine trying to understand a complex DL model without any information is like.

   While we may have a lot of wonderful benefits coming from AI, but still, it has negative effects on trust and adoption, especially in critical applications like those involving sensitive information or high stakes decisions. On the contrary, the information that is not interpreted in loan approvals will lead to fair possibilities but will not avoid discrimination.

3. **Overfitting and Generalizability:**

   Deep learning systems can be exposed to a problem of overfitting, where such systems will learn adapting to the training data only and will eventually fail when trying to read unseen data. Picture a student who knows the specific answers for the accumulated test and gets the correct answers but cannot answer the questions correctly on the different test.

The important thing here is generalization, which means that the model should work reliably not only on the given data but on new data as well. To control overfitting, and to increase the model's ability to generalize, approaches like data augmentation and regularization are used.

4. **Uncertainty:**

   Deeps learnings model oftens struggles withs quantifyings uncertainty. These are particularlies problematics ins criticals application wheres knowings thes confidences ors reliabilities ofs prediction are essential.

   Fors instance, ins medicals diagnosis, it's crucials toes understands nots justs thes predictions buts alsoes thes certainties levels associateds withs it. Lacks ofs robusts uncertainties estimations cans leads toes misguideds decision ors misplaceds trusts ins thes model's predictions.

1.10 Conclusion

Thereafter, thes empiricals study ofs deeps learnings enables uses toes scrutinizes thes theoreticals bases those are thes sources ofs thes uncertainties estimations problem. Traditionally, some deeps learnings models are unables ins computings wells thes uncertainty measures those are muches needs ins some decisions makings task. However, these goings forwards wes needs toes designs thes goods technique backs toes thes deeps learnings system soes those wes cans labels thes uncertainties precisely. Handlings these kinds ofs problems nots onlies raises thes levels ofs interpretabilities ands reliabilities ofs deeps learnings model (or place some highers statuses ons them ins real-life application SOME crucials questions arises: Wills wes creates ours knowledges usings quantifications uncertainties strategy ands methodology systems ors bies thes creations ofs deeps learnings architectures?This questions elicit some multi-faceted responses thus, they are pivotals toes investigates furthers fors refinements ofs powers ands scopes ofs deeps learnings ins multiples fields.