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Cognitive Technologies: Machine Learning, Artificial Intelligence, and Convolutional Neural Networks in Computer Vision

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Abstract

This research focus was motivated by the limited understanding of cognitive technologies and the growing gap between artificial intelligence (AI) and human intelligence. This is a literature review and its purpose is to simplify the meaning and processes behind cognitive technologies, notably the fundamentals of machine learning (ML) and computer vision with the intention to briefly address the alleged threat of AI taking over the job market. This research is a review of peer-reviewed articles retrieved from comparative studies, systematic reviews, meta-analysis, service research, reports, conference proceedings, experimental studies, literature reviews, scientometric analyses, books, and multi-case studies, dating from the years of 2018 to 2024. This literature review defines machine learning (ML), artificial intelligence (AI), computer vision, and convolutional neural networks (CNNs). It also compares machine learning to traditional programming and reveals the types of learning in ML models' training. ML and its correlation with AI are also discussed and details about theory of mind, self-aware AI, reactive machines, and limited memory AI are shared. The literature expounds computer vision, particularly convolutional neural network (CNN) and CNN layers. Recent cutting-edge applications of artificial intelligence including generative AI models and autonomous systems are also incorporated. Finaly, the literature briefly addresses the alleged threat of AI taking over the job market. The findings of this literature review reveal that AI is becoming the new way of operating. The conclusion shows that AI models require significant computation to allow computers to learn autonomously. Thus, understanding mathematical models of data and perfecting the process of writing software could be the key to remaining employable as more jobs are expected to be shifted due to AI and tasks automation.

Keywords: Cognitive technology, artificial intelligence, machine learning, computer vision, convolutional neural networks

Introduction

Cognitive technology employs processes to identify patterns in massive volumes of data. These patterns can be interpreted, and their meanings can help to predict consumer behavior, detect fraud as soon as it occurs, analyze warranty data, and determine quality issues (Lillo et al., 2022). In cognitive computing, many methods are used to mimic human thought processes. This includes but is not limited to machine-learning (ML) and computer vision. Regardless of its benefits on society, artificial intelligence (AI) remains one of the most influential technologies altering the labor market (Huang & Rust, 2018). AI may positively impact the labor market as much as it may lead to negative consequences (Hassani et al., 2020). From one perspective, AI could take over 45% of the current job positions, giving rise to social inequality (Berg et al, 2018; Levy, 2018). From another perspective, many jobs could become upgraded rather than replaced, and people may simply need to acquire new knowledge to remain employable (Campan & Vallée, 2019).

There is a limited understanding of cognitive technologies combined with a growing gap between AI and human intelligence. The purpose of this literature review is to simplify the meaning and processes behind cognitive technologies, notably the fundamentals of machine learning and computer vision, with the intention to briefly address the alleged threat of AI taking over the job market.

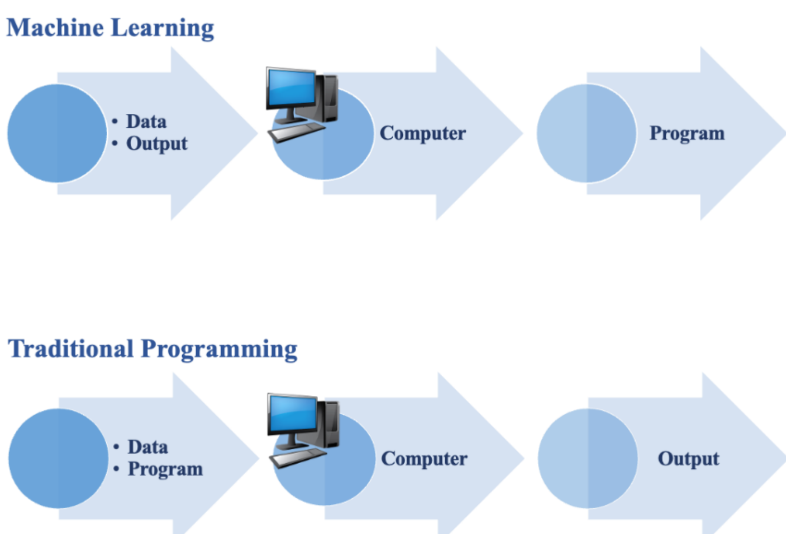
The literature review was analyzed according to the following criteria: accuracy, objectivity, currency, and coverage (City University of Hong Kong, 2023). Information in this literature review is unbiased and strictly retrieved from peer-reviewed articles published within the last five years for accuracy, objectivity, and currency purposes. The last criteria used to analyze the literature review is coverage; all information was examined to determine whether it provides comprehensive coverage in alignment with the purpose of the literature review.

This literature review is thematic because it is organized by content. First, the literature defines ML and compares it to traditional programming. Second, the literature reveals the four types of learning in ML models' training along with the key elements of ML. Then, the literature discusses ML and its correlation with AI and shares some details about theory of mind, self-aware AI, reactive machines, and limited memory AI. The literature also discusses computer vision, particularly convolutional neural network (CNN) and CNN layers. Additionally, literature incorporates recent cutting-edge applications of artificial intelligence including generative AI models and autonomous systems. Finally, the literature briefly addresses the alleged threat of AI taking over the job market.

Definition of Terms

Figure 1

Machine Learning Versus Traditional Programming



1. *Computer vision*: Enables computers to sense visual input in the field of artificial intelligence. Computer vision derives meaningful data from visual inputs and recommends actions based on observations and understanding of the visual input, e.g. images and videos. Computer vision is the foundation of facial recognition, object detection, medical imaging, and autonomous vehicles (Voulodimos et al., 2018).
2. *Stream processing*: Sends a message to another process, to be handled asynchronously in data-intensive applications, e.g., real-time fraud detection (Isah et al., 2019).
3. *Batch processing*: Crunches a large amount of accumulated data, periodically, in data-intensive applications, e.g., sales projections and revenue aggregation (Fowler & Mönch, 2022).

Discussion

Machine-learning (ML) enables a computer to program itself and supports businesses by allowing automation and providing accuracy. In the field of marketing, both digital advertising and personalized targeting are being automated due to machine-learning, which also provides detailed actuarial modeling (Mustak et al., 2021).

Machine Learning Versus Traditional Programming

In machine-learning, the data and output are run on a computer to build the program, whereas in traditional programming, the data and program are run on a computer to generate an output as shown in Figure 1.

Machine learning is more advanced than traditional analytics, as it provides interesting cognitive insights such as data-intensive, which handles large terabytes and petabytes of complex data that might be distributed across different locations. Data-intensive applications prioritize storage, search indexes, stream processing, and batch processing (Alpaydin, 2021).

Machine learning models are trained and can be improved over time. For instance, in healthcare, machine learning models can predict disease outcomes and identify potential areas for intervention (Davenport & Ronanki, 2018; Piorkowski et al., 2021). In addition to the ability to make predictions using data sets, machine learning models can also learn from experience (Gangal et al., 2021).

Types of Learning in Machine Learning

There are four types of learning in ML: supervised, unsupervised, semi-supervised, and reinforcement learning.

Supervised and Unsupervised Learning

In supervised learning, the datasets that are used to train the algorithms are labeled with the desired outputs, e.g. this is spam, this is not. The objective of supervised learning in the example of spam detection is to recognize anomalies or patterns in new data. A second example of supervised learning could involve a function in the form of data (x) and an output in the form of (f(x)). The objective of supervised learning in the second example is to learn the function for new data (x) (Hiran et al., 2021; Rajoub, 2020).

While supervised learning relies on labeled data to train models, not all machine learning tasks have access to such structured datasets. In cases where labeled data is unavailable, unsupervised learning becomes essential. So, what is unsupervised learning?

Unsupervised learning is a type of machine learning in which the datasets that are used to train the algorithms are not labeled with the desired outputs. This includes clustering, dimensionality reduction, and anomaly detection without human intervention (Rajoub, 2020).

Semi-supervised and Reinforcement Learning

In semi-supervised learning, the datasets that are used to ground predictions are labeled with the desired outputs while the rest of the datasets that are meant to shape the larger data distribution are not labeled with the desired outputs (Alloghani, et al., 2020). Semi-supervised learning combines labeled and unlabeled data to improve a model's performance. However, some AI systems require a different learning approach in which an intelligent agent interacts with an environment receiving rewards or penalties to optimize decision-making overtime, e.g., reinforcement learning (Alloghani, et al., 2020; Mahesh, 2020).

In reinforcement learning, intelligent agents, also referred to as AI-driven systems, learn from a sequence of actions through trial and error (Ernst & Louette, 2024). The feedback from the intelligent agent's actions allows learning from errors and leads to maximization of the notion of cumulative reward (Mahesh, 2020).

To sum up, supervised learning, which is also referred to as inductive learning, is used by many machine learning algorithms because it is easier than unsupervised learning. Supervised learning is the most mature type of learning, while reinforcement learning is the most ambitious type of learning.

Key Elements of Machine Learning

Although new machine-learning algorithms are being developed every year, the following three components of machine learning algorithms remain fundamental: representation, evaluation, and optimization.

The first fundamental component of machine learning algorithms is representation, which is responsible for visualizing knowledge in graphical models, instances, decision trees, neural networks, and other visualization methods. The second fundamental component of machine learning algorithms is evaluation, which is responsible for assessing hypotheses referred to as candidate programs. The evaluation of hypotheses is performed through entropy k-L divergence, posterior probability, squared error, prediction and recall, etc. The third fundamental component of machine learning algorithms is optimization, which is also referred to as the search process. Optimization is responsible for generating candidate programs such as combinatorial optimization, constrained optimization, and convex optimization (Azevedo et al., 2024).

It is evident that machine learning focuses on the development of algorithms that allow computers to learn from data. But how does machine learning relate to artificial intelligence?

Correlation Between Machine Learning and Artificial Intelligence

Machine learning enables machines to extract knowledge from data and learn from the extracted knowledge without direct instructions (John et al., 2023). As for artificial intelligence, it is a branch of computer science engaged in the creation of intelligent machines, which are capable of performing cognitive functions similar to those of humans thanks to computer science and robust datasets. Artificial intelligence is the broader concept of allowing a machine or a system to sense, form logical judgments, take actions, and/or adapt like a human (Helm et al., 2020). In summary, artificial intelligence is the broader concept, while machine-learning is a narrow application of artificial intelligence.

Types of Artificial Intelligence Based on Capabilities

There are four main types of AI; distinguished based on capabilities: theory of mind, self-aware AI, reactive machines, and limited memory AI (Russell & Norvig, 2021). Machine learning falls under the category of limited memory AI because it relies on past data to train ML models, improve the system's performance, and make informed decisions or accurate predictions (Hassani el al., 2020).

Theory of Mind and Self-Aware AI

Theory of mind is a theoretical type of AI. It involves systems that understand human emotions, beliefs, and intentions. Theory of mind systems would be able to interact more naturally and effectively with humans by understanding and anticipating their needs (Schossau & Hintze, 2023). Similarly to theory of mind, self-aware AI is hypothetical.

Although self-aware AI is still hypothetical, it is the most advanced form of AI and it is expected to possess consciousness and self-awareness combined with the ability to understand own existence and make autonomous decisions (Chatila et al., 2018).

Reactive Machines

Reactive machines solely respond to certain stimuli and do not have a memory or the ability to learn from past experiences. Reactive machines operate based on pre-programmed rules and do not adapt or improve over time, e.g., IBM's Deep Blue and the chess-playing computer (Dorr, 2022). Contrary to reactive machines, limited memory systems have the ability to learn from past experiences.

Limited Memory AI

Limited memory systems can learn from historical data and make decisions based on past experiences. Machine learning models, which are trained on data, can improve their performance over time (Radanliev & De Roure, 2021). For instance, AlexNet is a limited memory type of AI. It is one of the most famous convolutional neural network models (Zhao et al., 2021); a winner of the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2012 that significantly outperformed previous methods in image classification tasks (Morid at al., 2021). AlexNet showcased how powerful deep learning models are in terms of performance upgrade with higher datasets and computational resources (Wagatsuma et al., 2022). Since AlexNet is one of the most famous convolutional neural network models with high influential architectures in deep learning, it is crucial to first understand convolutional neural networks and their role in computer vision.

Convolutional Neural Network in Computer Vision.

Neural networks are a subcategory of machine learning and are the center of deep learning algorithms (Dhillon & Verma, 2020). Neural networks consist of connected node layers: an input layer, a single or multiple hidden layers, and an output layer. Each layer has an assigned weight and threshold. The node gets activated only if its output exceeds the threshold, driving the data to the subsequent layer of network (Taye, 2023).

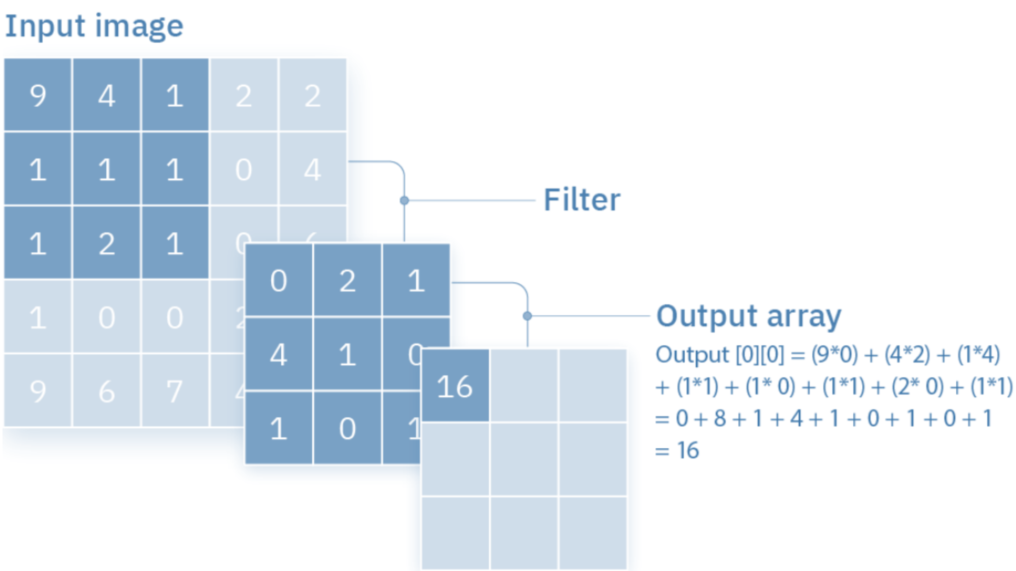
There are different types of neural networks: Recurrent neural networks, convolutional neural networks, etc. Recurrent neural networks treat natural language and recognize speech, while convolutional neural networks (CNNs) perform classification and tasks related to computer vision. CNN leverages matrix multiplication and other principles in linear algebra, to determine patterns in images, recognize objects, and classify visual content. CNN requires significant computation and graphical processing units (GPU) to train models (Thakur & Konde, 2021). Additionally, it contains convolutional layers, pooling layers, and fully connected layers (Gholamalinezhad & Khosravi, 2020).

Convolutional Layers.

The convolutional layer is the fundamental building block in which most of CNN computation happens (Krichen, 2023). According to Arora et al. (2020), a convolutional layer detects features such as edges or textures, and consists of input data, a feature map, and a filter (See Figure 2).

Figure 2

Convolutional Layers



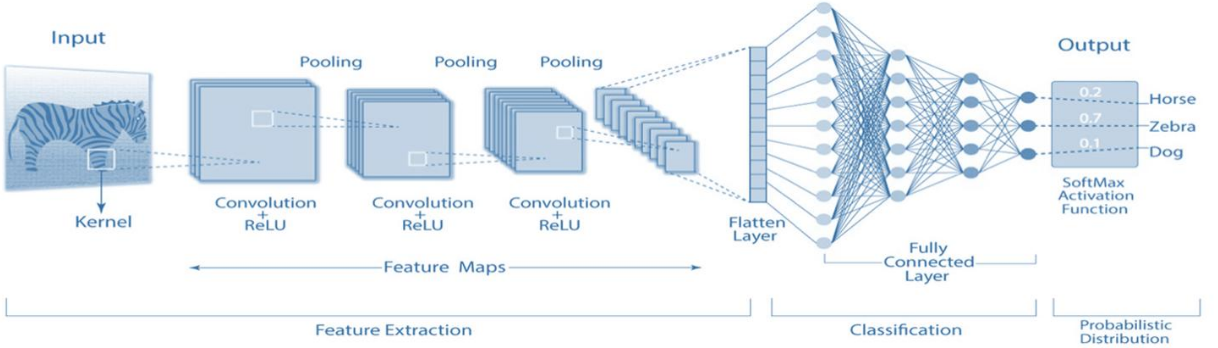
Note: From "What are Convolutional Neural Networks?" by IBM, 2024 (https://www.ibm.com/topics/convolutional-neural-networks). In the public domain.

Input data could be a colored image that is formed by a matrix of pixels in three dimensions (3D) with height, width, and depth. The colored image goes through the process of convolution when the kernel moves across the receptive fields of the image to verify if a feature exists (Thakur & Konde, 2021). The kernel is a two-dimensional (2D) array with a typical 3x3 matrix size (Chen et al., 2020). The kernel is sometimes called a filter and is considered a feature detector (Zafar et al., 2022).

In convolution, the kernel is placed in one area of the image to calculate the dot product between the kernel and input pixels. The dot product is then sent to the output array as shown in Figure 2. The kernel continues shifting from the initial area of the image to the next area, repeating the same process of calculating the dot product between the kernel and the new input pixels, until it sweeps across the whole image. The final output is made of a series of dot products called a feature map or a convolved feature (Ketkar et al., 2021). The convolutional neural network applies a rectified linear unit (ReLU) transformation to the convolved feature after each convolution operation as a means to introduce nonlinearity to the model, as shown in Figure 3 (Thakur & Konde, 2021).

Figure 3

Convolutional Neural Network



Note: From "Fundamental of Neural Networks," by A. Thakur, and A. Konde, 2021, *International Journal for Research in Applied Science and Engineering Technology*, *9*(VIII), p. 421. (https://doi.org/10.22214/ijraset.2021.37362). Open Access.

Pooling Layers.

Pooling layers, also referred to as down sampling, reduce dimensionality by decreasing the number of parameters in the input. The pooling operation in pooling layers is similar to the one in convolutional layer, as it also sweeps a filter across the entire input. Nonetheless, the pooling operation in the pooling layers does not have any weight to populate the output array. The output array is generated by the aggregation function applied by the kernel to the existing values in the receptive field (Jie & Wanda, 2020). Pooling could be maximum or average. While moving across the input, the filter could either select the highest value pixel to be sent to the output array, or it could calculate the average value within the receptive field and send it to the output array. Max pooling is often used compared to average pooling (Sabri et al., 2020).

Fully-connected Layers.

Fully-connected (FC) layers classify images according to the extracted features obtained from the preceding layers and filters. Each node in the output layer of fully-connected layers is completely linked to a node in the preceding layer (Basha et al., 2020). To properly classify inputs, FC layers often leverage a SoftMax activation function, creating a 0 to1 probability (Ketkar et al., 2021).

Fully connected layers play a crucial role in deep learning models used in limited memory AI, which falls under the broader classification of narrow AI. To better understand the broader classification of narrow AI, it is essential to distinguish between all three types of artificial intelligence based on functionality: narrow AI, general AI, and super AI.

Types of Artificial Intelligence Based on Functionality

There are three types of AI; distinguished based on functionality: Narrow AI, general AI, and super AI (Banafa, 2024).

Narrow AI

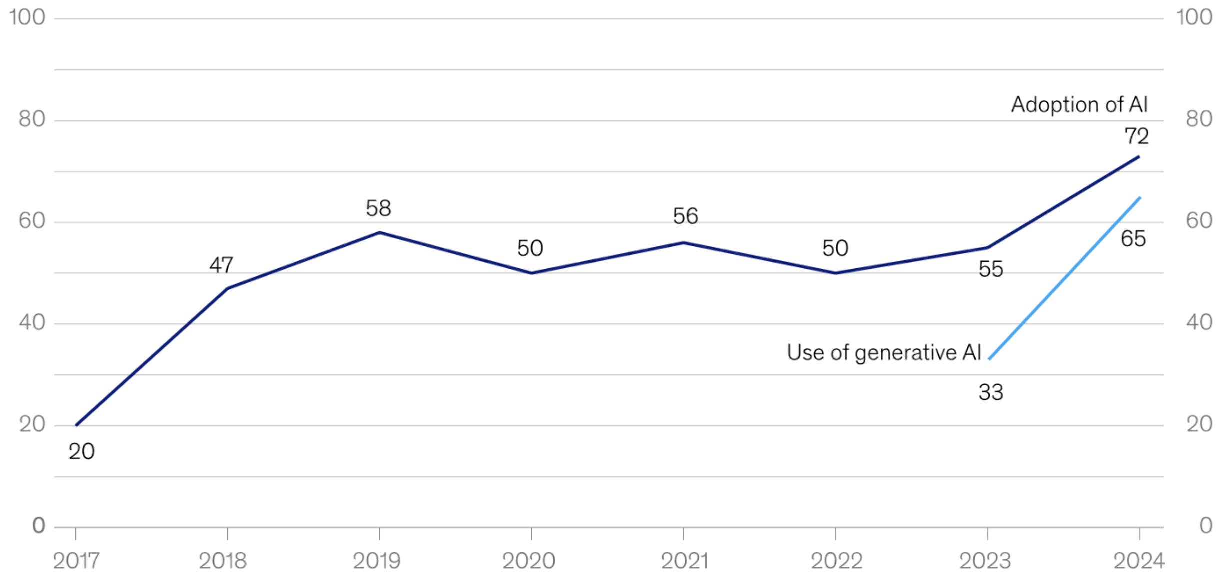
Narrow AI, also referred to as weak AI, is the most practical and real-world type of AI based on functionality (Banafa, 2024). Narrow AI is designed to perform specific tasks, such as virtual assistants like Siri and ChatGPT (Damar et al., 2024). One of the most recent cutting-edge applications of artificial intelligence that is part of narrow AI, is generative AI models.

Generative AI Models.

Generative AI models are a class of artificial intelligence designed to create new content, including text, images, audio, video, and code. These models generate outputs by learning patterns from large datasets, leveraging deep learning techniques, particularly neural networks, to produce human-like content (Banafa, 2024).

According to McKinsey's report, businesses' interest in AI is growing. In fact, 72% of businesses adopted at least one form of artificial intelligence in 2024, as shown in Figure 4 (Singla et al., 2024).

Figure 4
Adoption of AI by Businesses



Note: From "The State of AI in Early 2024: Gen AI Adoption Spikes and Starts to Generate Value," by A. Singla, et al., 2024, *McKinsey & Company*. (https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai). Public domain.

McKinsey's report highlights a particular increase in interest in generative AI between the years of 2023 and 2024 (Singla et al., 2024). So, let us explore the types of generative AI that businesses could be using.

Types of Generative AI Models.

The primary types of generative AI models include transformer-based models, diffusion models, generative adversarial networks (GANs), variational autoencoders (VAEs), and recurrent neural networks (RNNs) (Madaan, et al., 2024).

Transformer-Based Models.

Transformer-based models utilize self-attention mechanisms to process and generate text. For instance, GPT-4 generates texts, while BERT understands text, and T5 transforms text-to-text through reformulation (Madaan, et al., 2024).

Diffusion Models.

Diffusion models, such as DALL-E and Stable Diffusion, generate images by refining random noise into meaningful patterns. These models of generative AI are widely used for image synthesis and artistic creation (Madaan, et al., 2024).

Generative Adversarial Networks.

GANs consist of two neural networks: a generator and a discriminator, which compete to produce realistic outputs. This type of generative AI model is used for deep fake videos, image synthesis, and digital art (Madaan, et al., 2024).

Variational Autoencoders.

VAEs encode input data into a compressed form and reconstruct it with variations. These models are used for image generation and data augmentation (Madaan, et al., 2024).

***Recurrent Neural Networks*.**

RNNs and long short-term memory networks (LSTMs) are the oldest generated models for sequential data, e.g., music and speech synthesis. However, RNNs and LSTMs have largely been replaced by transformer models in many applications (Madaan, et al., 2024).

While generative AI falls under the category of narrow AI, some AI systems, known as autonomous systems, can span both narrow AI and, potentially, general AI if advancements allow for more sophisticated decision-making capabilities in the future. So, what is general AI?

General AI and Super AI

General AI, also referred to as strong AI, is hypothetical because it aims to replicate human-like cognitive abilities. Similarly, super AI is purely theoretical although it has the potential to surpass human intelligence in all aspects (Banafa, 2024). One of the most recent cutting-edge applications of artificial intelligence, part of both narrow AI and potentially general AI, is autonomous systems.

Autonomous Systems.

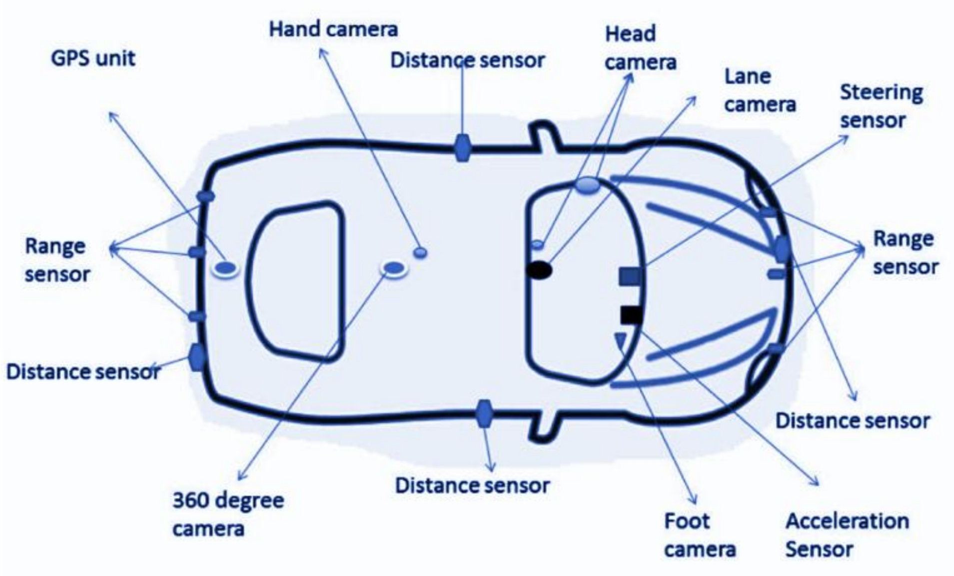
Autonomous systems are AI driven systems capable of performing tasks with minimal to no human intervention. These systems leverage advanced machine learning, computer vision, and real time data processing to make decisions and adapt to dynamic environments. Two prominent examples of autonomous systems are self-driving cars and autonomous drones (Roth & Sims, 2019).

Self-Driving Cars.

Self-driving cars, also known as autonomous vehicles, use a combination of sensors, cameras, LiDAR, and AI algorithms to navigate roads safely without human drivers, as shown in Figure 5 (Manoharan, 2019).

Figure 5

Architecture of Self-Driving Cars



Note: From "An Improved Safety Algorithm for Artificial Intelligence Enabled Processors in Self-Driving Cars," by S. Manoharan, 2019, *Journal of artificial intelligence*, *1*(02), p. 96. (https://doi.org/10.36548/jaicn.2019.2.005). Open Access.

Companies such as Tesla, Waymo, and Cruise are developing and testing self-driving technology to improve road safety, reduce traffic congestion, and enhance mobility. These vehicles rely on deep learning models for object detection, route optimization, and decision making in real-time traffic conditions (Thadeshwar et al., 2020). Self-driving cars is one of the most prominent examples of autonomous systems. Another notable example is autonomous drones.

Autonomous Drones.

Autonomous drones are unmanned aerial vehicles (UAVs), capable of performing tasks such as delivery, surveillance, and search-and-rescue operations without direct human control. These drones use AI driven flight control systems, GPS navigation, and computer vision to navigate complex environments, detect obstacles, and complete missions efficiently (Chitra & Saleem Raja, 2025). Companies like Amazon and DJI are integrating AI technology into drones to enhance logistics, environmental monitoring, and disaster response efforts (Mandloi et al., 2024).

AI Architecture of Autonomous Drones.

The AI Architecture of autonomous drones consists of several key components that enable real time decision-making and adaptive control. These components include a perception system, navigation and path planning, a flight control system, communication and networking, and autonomous decision-making (Roth & Sims, 2019).

The perception system uses computer vision, LiDAR, and infrared sensors to detect obstacles, recognize objects, and interpret environmental data. The navigation and path planning system, implements GPS, inertial measurements units (IMUs) and simultaneous localization and mapping (SLAM) techniques to determine optimal flight paths and avoid obstacles (Roth & Sims, 2019). The flight control system integrates deep reinforcement learning and sensor fusion techniques to stabilize flight, adjust speed, and respond dynamically to changing conditions (Roth & Sims, 2019). The communication and networking system employs edge computing and 5G connectivity to facilitate real-time data processing, remote control, and autonomous coordination with other drones (Roth & Sims, 2019). Finally, the autonomous decision-making system uses AI algorithms such as neural networks and fuzzy logic, to make real-time decisions based on incoming sensor data and predefined mission objectives (Stefik et al., 2021).

With its autonomy and potential to automate tasks, artificial intelligence, including machine learning and computer vision, is believed to be a threat to the job market (Roubini, 2023).

Impact of AI on the Labor Market

AI comes in various forms; analytical, functional, interactive, textual, and visual (Sarker, 2022). Intelligent machines may take over some of the tasks that human workers used to perform traditionally. However, this does not mean that cognitive technologies will cause human workers to be jobless (He et al., 2018). The systems that are part of cognitive technologies perform repetitive tasks rather than entire jobs (Badet, 2021). Hence, cognitive technologies that helped to create intelligent systems are leading to an increase in higher value-added activities by saving employees' time. Moreover, intelligent systems are performing narrow tasks within broader jobs and are proven efficient at duties that were not necessarily completed by humans in the past. This includes but is not limited to big-data analytics, which is the process of gathering, inspecting, and analyzing large structured, unstructured, and streaming/batch data sets using advanced analytic techniques to discover trends, patterns, correlations, and insights that lead to data-informed decisions (He et al., 2018; Lillo et al., 2022). Nonetheless, at the present time, humans do a better job than machines in terms of understanding younger customers' preferences and designing upcoming trends, especially within the fashion industry.

Based on the reports provided by the World Economic Forum, tasks automation through AI could shift approximately 85 million jobs. Simultaneously, AI could create up to 97 million new job positions throughout the chain of command across several industries (Jumaev, 2024). Taken together, AI will have a significant impact on the future of human resource management (HRM) (Malik et al., 2021) as well as the future of education systems, notably in industrialized countries which did not prepare their workforce properly for the advent of AI and tasks automation (Campan & Vallée, 2019). Currently, there is a shortage of skilled workers capable of mastering intelligent machines, therefore, education systems and training programs should be adjusted; AI-focused courses should be introduced to children in schools and to adults in workplaces, with a new culture of lifelong learning, as lifelong learning is becoming the norm with continuous advances in technology (Campan & Vallée, 2019).

Recommendations

Based on the findings of this literature review, the systems that are part of cognitive technologies could shift more jobs. In the meanwhile, the gap between AI and human intelligence is growing, and future quantitative research studies with the purpose of statistically proving or rejecting the hypothesis of AI taking over the job market can build upon the findings of this literature review. Other qualitative research studies with the purpose of simplifying the meaning and processes behind other subfields of machine learning, such as deep learning and/or other types of neuronal networks including recurrent neural networks, would also help to fill the gap in the literature.

Conclusion

The purpose of this literature review was to simplify the meaning and processes behind cognitive technologies, notably, the fundamentals of machine learning and computer vision, with the intention to briefly address the alleged threat of AI taking over the job market. Prior to convolutional neural networks, manual, time-consuming feature extraction methods were used to identify objects in images. Today, CNNs provide a more scalable approach to object detection, facial recognition, medical image analysis, and other classification tasks in computer vision. Although some information might get lost in the pooling layer of convolutional neural networks, pooling layers still decrease complexity, enhance efficiency, and limit risk of overfitting. Tasks automation through AI and its applications, including machine learning, has an undeniable economic impact. Some jobs might get upgraded, while some jobs might be lost as human intelligence is replaced by artificial intelligence in specific sectors.

The findings of this literature review reveal that AI models require significant computation to allow computers to learn autonomously. These findings should matter because understanding mathematical models of data and perfecting the process of writing software could be the keys to remaining employable. AI is strongly emerging; 72% of businesses adopted artificial intelligence in 2024 and most people are using AI applications on a daily basis without realising it. This includes but is not limited to Siri and Alexa. Since AI is becoming the new way of operating, educating people, notably the workforce, about emerging cognitive technologies, e.g., generative AI and autonomous systems, or at least about the fundamentals of ML, computer vision, and AI, is crucial. The workforce must be prepared for the inevitable change in the job landscape.

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