© December 2022| IJIRT | Volume 9 Issue 7 | ISSN: 2349-6002

What is the Future of AI?

Siddhesh Shinde
Keraleeya Samajam's Model College, Dombivli East, Mumbai, Maharashtra, India

***Abstract* - Artificial intelligence is the ability of machines to perform certain tasks, which need the intelligence showcased by humans and animals. This definition is often ascribed to Marvin Minsky and John McCarthy from the 1950s, who were also known as the fathers of the field. Artificial intelligence allows machines to understand and achieve specific goals. AI includes machine learning via deep learning. The former refers to machines automatically learning from existing data without being assisted by human beings. Deep learning allows the machine to absorb huge amounts of unstructured data such as text, images, and audio.73% of all Organizations have at least one application or a portion of their Infrastructure uses AI. 15% of enterprises intend to adopt AI in the next twelve months.**

I.INTRODUCTION

Artificial intelligence allows machines to model, and even improve upon, the capabilities of the human mind. From the development of self-driving cars to the proliferation of smart assistants like Siri and Alexa, AI is a growing part of everyday life. As a result, many tech companies across various industries are investing in artificially intelligent technologies.

The major limitation in defining AI as simply "building machines that are intelligent" is that it doesn't actually explain what AI is and what makes a machine intelligent. AI is an interdisciplinary science with multiple approaches, but advancements in machine learning and deep learning are creating a paradigm shift in virtually every sector of the tech industry. When one considers the computational costs and the technical data infrastructure running behind artificial intelligence, actually executing on AI is a complex and costly business. Fortunately, there have been massive advancements in computing technology, as indicated by Moore's Law, which states that the number of transistors on a microchip doubles about every two years while the cost of computers is halved. Although many experts believe that Moore's Law will likely come to an end sometime in the 2020s, this has had a major impact on modern AI techniques — without it, deep learning would be out of the question, financially speaking. Recent research found that AI innovation has actually outperformed Moore's Law, doubling every six months or so as opposed to two years. By that logic, the advancements artificial intelligence has made across a variety of industries have been major over the last several years. And the potential for an even greater impact over the next several decades seems all but inevitable.

Today, the most advanced AI technology to date is deep learning, a technique where scientists train machines by feeding them different kinds of data. Over time, the machine makes decisions, solves problems, and performs other kinds of tasks on their own based on the data set given to them.

II.TYPES OF AI

AI is divided into four classes, supporting the sort and complexity of the tasks a system is ready to perform. For instance, machine-controlled spam filtering falls into the foremost basic category of AI, whereas the far potential for machines that will understand people's thoughts and emotions is a component of a completely totally different AI set.

Reactive Machine

A reactive machine follows the foremost basic of AI principles and, as its name implies, is capable of solely victimization its intelligence to understand and react to the globe ahead of it. A reactive machine cannot store memory and, as a result, cannot place confidence in past experiences to tell higher cognitive processes in real-time. Perceiving the globe directly implies that reactive machines square measure designed to finish solely a restricted range of specialized duties. By choice narrowing a reactive machine's worldview isn't any kind of cost-cutting life, however, and instead implies that this kind of AI is going to be additional trustworthy and reliable — it'll react a similar thanks to similar stimuli whenever. A notable example of a reactive machine is Deep Blue which was designed by IBM in the Nineties as a chess-playing mainframe computer and defeated grandmaster Gary Kasparov during a game. Deep Blue was solely capable of distinguishing the items on a chess board and knowing that everyone moves supported the principles of chess, acknowledging every piece's gift position and deciding what the foremost logical move would be at that moment. The PC wasn't following future potential moves by its opponent or making an attempt to place its own items in higher positions. Each flip was viewed as its own reality, breaking away from the other movement that was created beforehand. Another example of a game-playing reactive machine is Google's AlphaGo. AlphaGo is additionally incapable of evaluating future moves however depends on its own neural network to gauge developments of the current game, giving it a footing over Deep Blue during a additional complicated game. AlphaGo additionally best competitors of the sport, defeating champion Go player Lee Sedol in 2016. Though restricted in scope and not simply altered, reactive machine AI will attain level of quality, and offers reliableness once created to meet repeatable tasks.

Machine Learning and Deep Learning

Much of slender AI is high-powered by breakthroughs in ML and deep learning. Understanding the distinction between AI, ML and deep learning is confusing. VC Frank Chen provides an honest summary of the way to distinguish between them, noting: Simply put, an ML algorithmic rule is fed knowledge by a machine, and uses applied math techniques to assist it in "learning" the way to get higher and higher accuracy at a task, while not essentially having been specifically programmed for that task. Instead, Machine Learning algorithms use historical knowledge as input to predict new output values. To finish, machine learning consists of each supervised learning (where the expected output is more accurate because of labeled input knowledge sets) and unsupervised learning (where the expected outputs not that accurate or not predictable due to untagged knowledge sets). Machine learning is current world throughout standard of living. Google Maps uses location knowledge from smartphones, also as user-reported knowledge on things like construction and automotive accidents, to observe the ebb and flow of traffic and assess what the quickest route is going to be. Personal assistants like Siri, Alexa and Cortana measure ready to set reminders, hunt for on-line data and management, the lights in people's homes all with the assistance of machine learning algorithms that collect a set of data, learn a user's preferences, and improve their expertise supported previous interactions with users. Even Snapchat filters use machine learning algorithms to identify users' facial activity. Meanwhile, deep learning could be a sort of machine learning that runs inputs through a biologically-inspired neural specification. The neural networks contain a variety of hidden layers through which the information is processed, permitting the machine to travel "deep" in its learning phase, creating connections and assigning weight input for the most accurate results. Self-driving cars use deep learning to understand outside objects and vehicle speed, since they use deep neural networks to discover objects around them, confirm their distance from alternative cars, and determine traffic signals and far a lot of. The wearable sensors and devices employed in the health care business additionally apply deep learning to assess the health condition of the patient, together with their blood glucose levels, pressure and rate. They'll additionally derive patterns from a patient's previous medical knowledge and use that to anticipate any future health conditions.

Reinforcement

Alongside its important role in the development of deep learning, neuroscience was also instrumental in erecting the second pillar of contemporary AI, stimulating the emergence of the field of reinforcement learning (RL). RL methods address the problem of how to maximize future reward by mapping states in the environment to actions and are among the most widely used tools in AI research Although it is not widely appreciated among AI researchers, RL methods were originally inspired by research into animal learning. In particular, the development of temporal-difference (TD) methods, a critical component of many RL models, was inextricably intertwined with research into animal behavior in conditioning experiments. TD methods are real-time models that learn from differences between temporally successive predictions, rather than having to wait until the actual reward is delivered. Of particular relevance was an effect called second-order conditioning, where affective significance is conferred on a conditioned stimulus (CS) through association with another CS rather than directly via association with the unconditioned stimulus. TD learning provides a natural explanation for second-order conditioning and indeed has gone on to explain a much wider range of findings from neuroscience,

III.FUTURE OF AI

Understanding of the Physical World

Recent perspectives emphasize key ingredients of human intelligence that are already well-developed in human infants
but lacking in most AI systems. Among these capabilities is knowledge of core concepts relating to the physical world, such as space, number, and objectness, which allow people to construct compositional mental models that can guide inference and prediction AI research has begun to explore methods for addressing this challenge. For example, novel neural network architectures have been developed that interpret and reason about scenes in a humanlike way, by decomposing them into individual objects and their relations. In other work, deep RL has been used to capture the processes by which children gain a commonsense understanding of the world through interactive experiments. Relatedly, deep generative models have been developed that are able to construct rich object models from raw sensory inputs. These leverage constraints first identified in neuroscience, such as redundancy reduction, which encourage the emergence of disentangled representations of independent factors such as shape and position. Importantly, the latent representations learned by such generative models exhibit compositional properties, supporting flexible transfer to novel tasks.

Transfer Learning

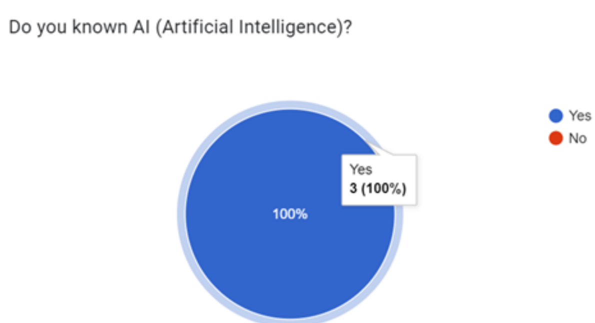
Humans also excel at generalizing or transferring generalized knowledge gained in one context to novel, previously
unseen domains. For example, a human who can drive a car, use a laptop computer, or chair a committee meeting is usually able to act effectively when confronted with an unfamiliar
vehicle, operating system, or social situation. Progress is being made in developing AI architectures capable of exhibiting strong generalization or transfer, for example by enabling zero-shot inferences about novel shapes outside the training distribution based on compositional representations. Others have shown that a new class of architecture, known as a progressive network, can leverage knowledge gained in one video game to learn rapidly in another, promising the sort of "far transfer" that is characteristic of human skill acquisition.

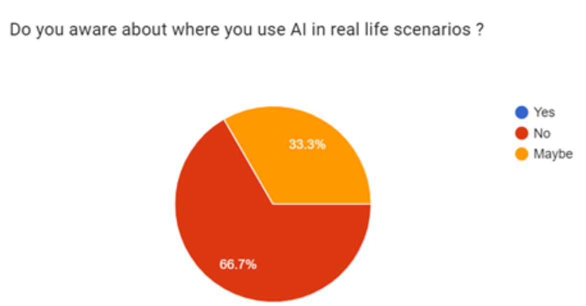
Progressive networks have also been successfully employed to transfer knowledge from a simulated robotic environment
to a real robot arm, massively reducing the training time required in the real world. Intriguingly, the proposed architecture bears some resemblance to a successful computational model of sequential task learning in
humans. In the neuroscience literature, one hallmark of transfer learning has been the ability to reason relationally, and AI researchers have also begun to make progress in building deep networks that address problems of this nature, for example by solving visual analogies. More generally, however, how humans or other animals achieve this sort of high-level transfer learning is unknown and remains a relatively unexplored topic in neuroscience. New advances on this front could provide critical insights to spur AI research toward the goal of lifelong learning in agents, and we encourage neuroscientists to engage more deeply with this question. At the level of neural coding, this kind of transfer of abstract structured knowledge may rely on the formation of
conceptual representations that are invariant to the objects, individuals, or scene elements that populate a sensory
domain but code instead for abstract, relational information among patterns of inputs. However, we currently lack direct evidence for the existence of such codes in the mammalian brain. Nevertheless, one recent report made the very interesting claim that neural codes thought to be important in the representation of allocentric (map-like) spaces might be critical for abstract reasoning in more general domains. In the
mammalian entorhinal cortex, cells encode the geometry of allocentric space with a periodic "grid" code, with receptive fields that tile the local space in a hexagonal pattern. Grid codes may be an excellent candidate for organizing conceptual knowledge, because they allow state spaces to be decomposed

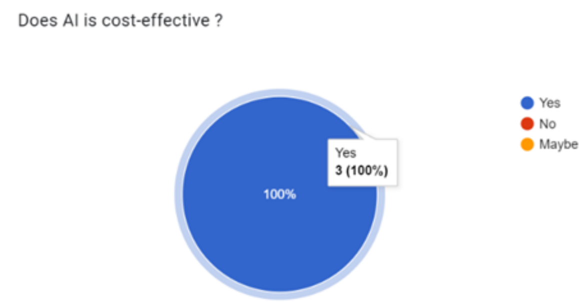
efficiently, in a way that could support the discovery of subgoals and hierarchical planning. Using functional neuroimaging, the researchers provide evidence for the existence of such codes while humans performed an abstract
categorization task, supporting the view that periodic encoding is a generalized hallmark of human knowledge
organization. However, much further work is required to substantiate this interesting claim.

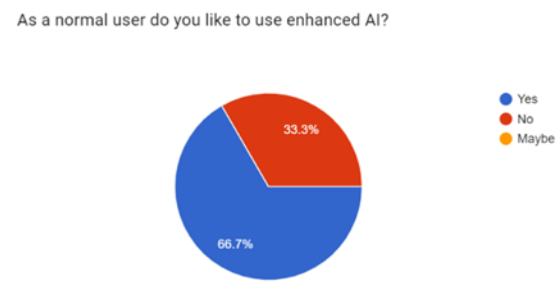
Virtual Brain Analytics
One rather totally different method during which neurobiology might serve AI is by furnishing new analytic tools for understanding computation in AI systems. thanks to their quality, the product of AI analysis usually stays in “black boxes”; we tend to understand solely poorly the character of the computations that occur, or representations that are unit shaped, throughout learning of complicated tasks. However, by applying tools from neurobiology to AI systems, artificial equivalents of single-cell recording, neuroimaging, and lesion techniques, we are able to gain insights into the key drivers of booming learning in AI research and increase the interpretability of those systems. we tend to decide on this “virtual brain analytics.”

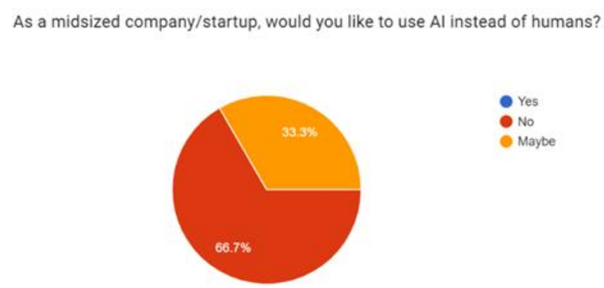
IV.SURVEY RESULTS











V. CONCLUSION

Artificial Intelligence and the technology are one side of the life that always interest and surprise us with the new ideas, topics, innovations, products …etc. AI is still not implemented as the films representing it(i.e. intelligent robots), however there are many important tries to reach the level and to compete in market, like sometimes the robots that they show in TV. Nevertheless, the hidden projects and the development in industrial companies.
This is not the end of AI, there is more to come from it, who knows what the AI can do for us in the future, maybe it will be a whole society of AI.

REFERENCE

[1] Link:- https://www.nist.gov/artificial-intelligence
[2] Link :- https://emeritus.org/in/learn/what-is-artificial-intelligence/
[3] Link:- https://egfound.org/projects/digital-revolution-technology-power-you/