iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 9 Issue: VIII Month of publication: August 2021

DOI: https://doi.org/10.22214/ijraset.2021.37597

www.ijraset.com

Call: 08813907089 | E-mail ID: ijraset@gmail.com

An Overview on Neural Network and Its Application

Subhash Kumar Sharma[1], Shikha Srivastava[2]
[1, 2]Department of Electronics, MGPG College, Gorakhpur

***Abstract:** In this paper an overview on neural network and its application is focused. In Real-world business applications for neural networks are booming. In some cases, NNs have already become the method of choice for businesses that use hedge fund analytics, marketing segmentation, and fraud detection. Here are some neural network innovators who are changing the business landscape. Here shown that how the biological model of neural network functions, all mammalian brains consist of interconnected neurons that transmit electrochemical signals. Neurons have several components: the body, which includes a* **nucleus** *and* **dendrites;** **axons,** *which connect to other cells; and axon* **terminals** *or* **synapses,** *which transmit information or stimuli from one neuron to another. Combined, this unit carries out communication and integration functions in the nervous system.*
***Keywords:** Neurons, neural network, biological model of neural network functions*

I. INTRODUCTION

A. *What Are Neural Networks?*

A branch of machine learning, *neural networks* (NN), also known as *artificial neural networks* (ANN), are computational models — essentially algorithms. Neural networks have a unique ability to extract meaning from imprecise or complex data to find patterns and detect trends that are too convoluted for the human brain or for other computer techniques. Neural networks have provided us with greater convenience in numerous ways, including through ridesharing apps, Gmail smart sorting, and suggestions on Amazon. The most ground breaking aspect of neural networks is that once trained, they learn on their own. In this way, they emulate human brains, which are made up of neurons, the fundamental building block of both human and neural network information transmission. "Human brains and artificial neural networks do learn similarly," explains Alex Cardinell, Founder and CEO of Cortx, an artificial intelligence company that uses neural networks in the design of its natural language processing solutions, including an automated grammar correction application, Perfect Tense. "In both cases, neurons continually adjust how they react based on stimuli. If something is done correctly, you'll get positive feedback from neurons, which will then become even more likely to trigger in a similar, future instance. Conversely, if neurons receive negative feedback, each of them will learn to be less likely to trigger in a future instance," he notes.

II. A BRIEF HISTORY OF NEURAL NETWORKS

Neural networks date back to the early 1940s when mathematicians Warren McCulloch and Walter Pitts built a simple algorithm-based system designed to emulate human brain function. Work in the field accelerated in 1957 when Cornell University's Frank Rosenblatt conceived of the *perceptron*, the ground breaking algorithm developed to perform complex recognition tasks. During the four decades that followed, the lack of computing power necessary to process large amounts of data put the brakes on advances. In the 2000s, thanks to the advent of greater computing power and more sophisticated hardware, as well as to the existence of vast data sets to draw from, computer scientists finally had what they needed, and neural networks and AI took off, with no end in sight. To understand how much the field has expanded in the new millennium, consider that ninety percent of internet data has been created since 2016. That pace will continue to accelerate, thanks to the growth of the Internet of Things (IoT).
For more background and an expansive timeline, read
"The Definitive Guide to Machine Learning: Business Applications, Techniques, and Examples."

A. *Why Do We Use Neural Networks?*

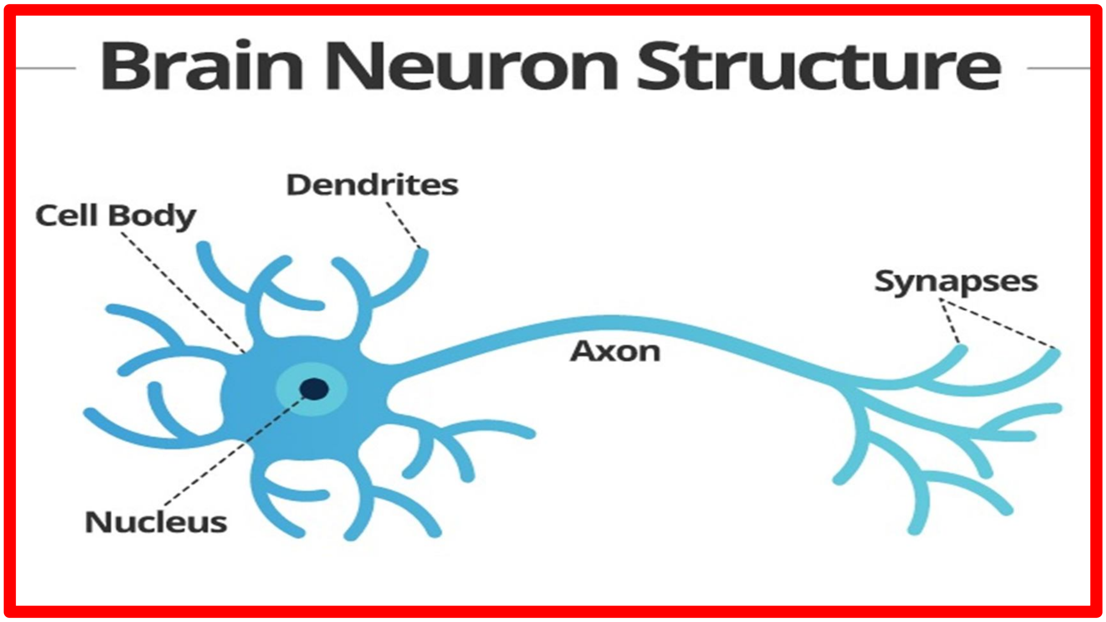
Neural networks' human-like attributes and ability to complete tasks in infinite permutations and combinations make them uniquely suited to today's big data-based applications. Because neural networks also have the unique capacity (known as *fuzzy logic*) to make sense of ambiguous, contradictory, or incomplete data, they are able to use controlled processes when no exact models are available. According to a report published by Statista, in 2017, global data volumes reached close to 100,000 petabytes (i.e., one million gigabytes) per month; they are forecasted to reach 232,655 petabytes by 2021. With businesses, individuals, and devices generating vast amounts of information, all of that big data is valuable, and neural networks can make sense of it.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.429
Volume 9 Issue VIII Aug 2021- Available at www.ijraset.com

III. HOW THE BIOLOGICAL MODEL OF NEURAL NETWORKS FUNCTIONS

What are neural networks emulating in human brain structure, and how does training work?

All mammalian brains consist of interconnected neurons that transmit electrochemical signals. Neurons have several components: the body, which includes a *nucleus* and *dendrites*; *axons*, which connect to other cells; and axon *terminals* or *synapses*, which transmit information or stimuli from one neuron to another. Combined, this unit carries out communication and integration functions in the nervous system. The human brain has a massive number of processing units (86 billion neurons) that enable the performance of highly complex functions.



IV. HOW ARTIFICIAL NEURAL NETWORKS FUNCTION

ANNs are statistical models designed to adapt and self-program by using learning algorithms in order to understand and sort out concepts, images, and photographs. For processors to do their work, developers arrange them in layers that operate in parallel. The *input layer* is analogous to the dendrites in the human brain's neural network. The *hidden layer* is comparable to the cell body and sits between the input layer and *output layer* (which is akin to the synaptic outputs in the brain). The hidden layer is where artificial neurons take in a set of inputs based on *synaptic weight*, which is the amplitude or strength of a connection between nodes. These weighted inputs generate an output through a transfer function to the output layer.

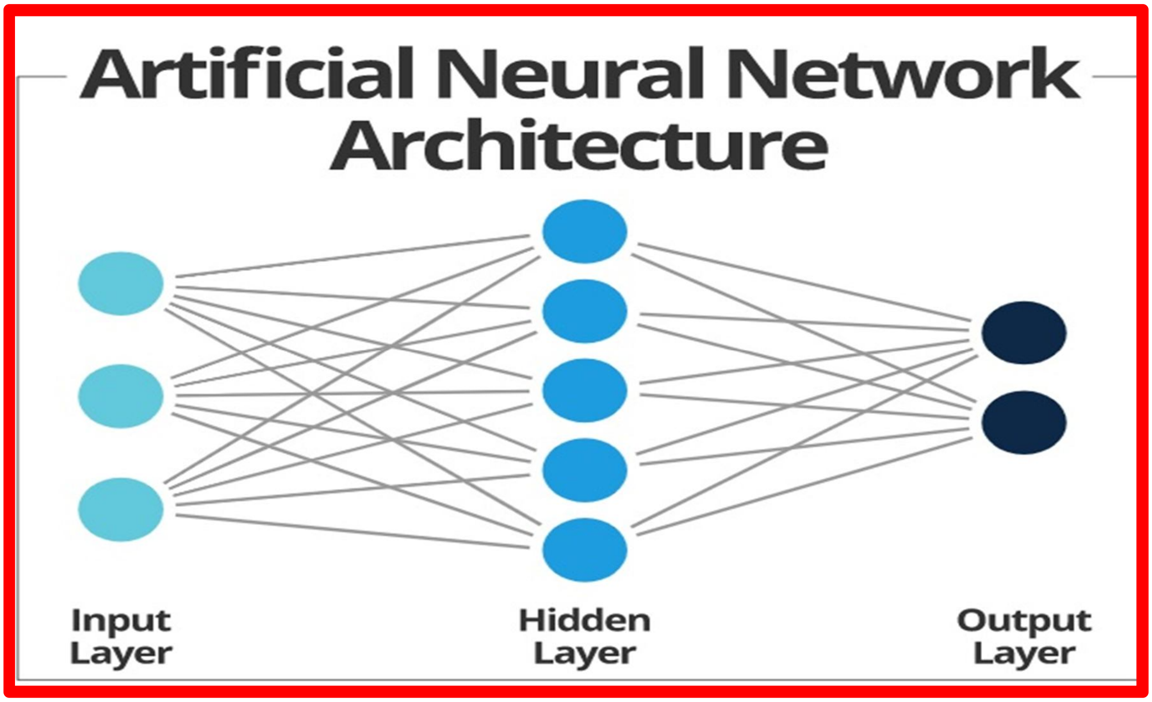
A. How Do You Train a Neural Network?

Once you've structured a network for a particular application, training (i.e., learning), begins. There are two approaches to training. *Supervised learning* provides the network with desired outputs through manual grading of network performance or by delivering desired outputs and inputs. *Unsupervised learning* occurs when the network makes sense of inputs without outside assistance or instruction.

There's still a long way to go in the area of unsupervised learning. "Getting information from unlabeled data, [a process] we call unsupervised learning, is a very hot topic right now, but clearly not something we have cracked yet. It's something that still falls in the challenge column," observes Université de Montréal's Yoshua Bengio in the article
" The Rise of Neural Networks and Deep Learning in Our Everyday Lives."

Bengio is referring to the fact that the number of neural networks can't match the number of connections in the human brain, but the former's ability to catch up may be just over the horizon. Moore's Law, which states that overall processing power for computers will double every two years, gives us a hint about the direction in which neural networks and AI are headed. Intel CEO Brian Krzanich affirmed at the 2017 Computer Electronics Show that "Moore's Law is alive and well and flourishing." Since its inception in the mid-20th century, neural networks' ability to "think" has been changing our world at an incredible pace.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.429
Volume 9 Issue VIII Aug 2021- Available at www.ijraset.com



V. ATTRIBUTES OF NEURAL NETWORKS

With the human-like ability to problem-solve — and apply that skill to huge datasets — neural networks possess the following powerful attributes:

1) *Adaptive Learning:* Like humans, neural networks model non-linear and complex relationships and build on previous knowledge. For example, software uses adaptive learning to teach math and language arts.
2) *Self-Organization:* The ability to cluster and classify vast amounts of data makes neural networks uniquely suited for organizing the complicated visual problems posed by medical image analysis.
3) *Real-Time Operation:* Neural networks can (sometimes) provide real-time answers, as is the case with self-driving cars and drone navigation.
4) *Prognosis:* NN's ability to predict based on models has a wide range of applications, including for weather and traffic.

VI. TASKS NEURAL NETWORKS PERFORM

Neural networks are highly valuable because they can carry out tasks to make sense of data while retaining all their other attributes. Here are the critical tasks that neural networks perform:

1) *Classification:* NNs organize patterns or datasets into predefined classes.
2) *Prediction:* They produce the expected output from given input.
3) *Clustering:* They identify a unique feature of the data and classify it without any knowledge of prior data.
4) *Associating:* You can train neural networks to "remember" patterns. When you show an unfamiliar version of a pattern, the network associates it with the most comparable version in its memory and reverts to the latter.

Neural networks are fundamental to *deep learning*, a robust set of NN techniques that lends itself to solving abstract problems, such as bioinformatics, drug design, social network filtering, and natural language translation. Deep learning is where we will solve the most complicated issues in science and engineering, including advanced robotics. As neural networks become smarter and faster, we make advances on a daily basis.

VII. REAL-WORLD AND INDUSTRY APPLICATIONS OF NEURAL NETWORKS

As an August 2018 New York Times article notes, "The companies and government agencies that have begun enlisting the automation software run the gamut. They include General Motors, BMW, General Electric, Unilever, MasterCard, Manpower, FedEx, Cisco, Google, the Defense Department, and NASA." We're just seeing the beginning of neural network/AI applications changing the way our world works.

H3: Engineering Applications of Neural Networks

Engineering is where neural network applications are essential, particularly in the "high assurance systems that have emerged in various fields, including flight control, chemical engineering, power plants, automotive control, medical systems, and other systems that require autonomy."

(Source: Application of Neural Networks in High Assurance Systems: A Survey.)

We asked two experts in the engineering sector about how their applications improve retail,
manufacturing, oil and gas, navigation, and information retrieval in office environments.

VIII. BUSINESS APPLICATIONS OF NEURAL NETWORKS

Real-world business applications for neural networks are booming. In some cases, NNs have already become the method of choice for businesses that use hedge fund analytics, marketing segmentation, and fraud detection. Here are some neural network innovators who are changing the business landscape.

At a time when finding qualified workers for particular jobs is becoming increasingly difficult, especially in the tech sector, neural networks and AI are moving the needle. Ed Donner, Co-Founder and CEO of untapt, uses neural networks and AI to solve talent and human resources challenges, such as hiring inefficiency, poor employee retention, dissatisfaction with work, and more. "In the end, we created a deep learning model that can match people to roles where they're more likely to succeed, all in a matter of milliseconds," Donner explains.

"Neural nets and AI have incredible scope, and you can use them to aid human decisions in any sector. Deep learning wasn't the first solution we tested, but it's consistently outperformed the rest in predicting and improving hiring decisions. We trained our 16-layer neural network on millions of data points and hiring decisions, so it keeps getting better and better. That's why I'm an advocate for every company to invest in AI and deep learning, whether in HR or any other sector. Business is becoming more and more data driven, so companies will need to leverage AI to stay competitive," Donner recommends.

The field of neural networks and its use of big data may be high-tech, but its ultimate purpose is to serve people. In some instances, the link to human benefits is very direct, as is the case with OKRA's artificial intelligence service.

Here are further current examples of NN business applications:

1) *Banking:* Credit card attrition, credit and loan application evaluation, fraud and risk evaluation, and loan delinquencies
2) *Business Analytics:* Customer behavior modeling, customer segmentation, fraud propensity, market research, market mix, market structure, and models for attrition, default, purchase, and renewals
3) *Defense:* Counterterrorism, facial recognition, feature extraction, noise suppression, object discrimination, sensors, sonar, radar and image signal processing, signal/image identification, target tracking, and weapon steering
4) *Education:* Adaptive learning software, dynamic forecasting, education system analysis and forecasting, student performance modeling, and personality profiling
5) *Financial:* Corporate bond ratings, corporate financial analysis, credit line use analysis, currency price prediction, loan advising, mortgage screening, real estate appraisal, and portfolio trading
6) *Medical:* Cancer cell analysis, ECG and EEG analysis, emergency room test advisement, expense reduction and quality improvement for hospital systems, transplant process optimization, and prosthesis design
7) *Securities:* Automatic bond rating, market analysis, and stock trading advisory systems
8) *Transportation:* Routing systems, truck brake diagnosis systems, and vehicle scheduling

The use of neural networks seems unstoppable. "With the advancement of computer and communication technologies, the whole process of doing business has undergone a massive change. More and more knowledge-based systems have made their way into a large number of companies," researchers Nikhil Bhargava and Manik Gupta found in "Application of Artificial Neural Networks in Business Applications."

A. What Are the Types of Neural Networks?

Neural networks are sets of algorithms intended to recognize patterns and interpret data through clustering or labeling. In other words, neural networks are algorithms. A *training algorithm* is the method you use to execute the neural network's learning process. As there are a huge number of training algorithms available, each consisting of varied characteristics and performance capabilities, you use different algorithms to accomplish different goals. Collectively, machine learning engineers develop many thousands of new algorithms on a daily basis. Usually, these new algorithms are variations on existing architectures, and they primarily use training data to make projections or build real-world models.

IX. THE CHALLENGES OF NEURAL NETWORKS

Cortx's Cardinell says that the value and implementation of neural networks depend on the task, so it's important to understand the challenges and limitations: "Our general approach is to do what works for each specific problem we're trying to solve. In many of those cases, that involves using neural networks; in other cases, we use more traditional approaches." Cardinell illustrates his point with this example: "For instance, in Perfect Tense, we try to detect whether someone is using *a* or *an* correctly. In this case, using a neural network would be overkill, because you can simply look at the phonetic pronunciation to make the determination (e.g., *an banana* is wrong). Neural networks are where most advances are being made right now. Things that were impossible only a year or two ago regarding content quality are now a reality."

As useful as neural networks can be, challenges in the field abound:

1) *Training:* A common criticism of neural networks, particularly in robotics applications, is that excessive training for real-world operations is mandatory. One way to overcome that hurdle is by randomly shuffling training examples. Using a numerical optimization algorithm, small steps — rather than large steps — are taken to follow an example. Another way is by grouping examples in so-called mini-batches. Improving training efficiencies and convergence capabilities is an ongoing research area for computer scientists.
2) *Theoretical Issues:* Unsolved problems remain, even for the most sophisticated neural networks. For example, despite its best efforts, Facebook still finds it impossible to identify all hate speech and misinformation by using algorithms. The company employs thousands of human reviewers to resolve the problem. In general, because computers aren't human, their ability to be genuinely creative — prove math theorems, make moral choices, compose original music, or deeply innovate — is beyond the scope of neural networks and AI.
3) *Inauthenticity:* The theoretical challenges we address above arise because neural networks don't function exactly as human brains do — they operate merely as a simulacrum of the human brain. The specifics of how mammalian neurons code information is still an unknown. Artificial neural networks don't strictly replicate neural function, but rather use biological neural networks as their inspiration. This process allows statistical association, which is the basis of artificial neural networks. An ANN's learning process isn't identical to that of a human, thus, its inherent (at least for now) limitations.
4) *Hardware Issues:* This century's focus on neural networks is due to the million-fold increase in computing power since 1991. More hardware capacity has enabled greater multi-layering and subsequent deep learning, and the use of parallel graphics processing units (GPUs) now reduces training times from months to days. Despite the great strides of NNs in very recent years, as deep neural networks mature, developers need hardware innovations to meet increasing computational demands. The search is on, and new devices and chips designed specifically for AI are in development. A 2018 *New York Times* article,
5) "Big Bets on A.I. Open a New Frontier for Chip Startups, Too," reported that "venture capitalists invested more than $1.5 billion in chip startups" in 2017.
6) *Hybrids:* A proposal to overcome some of the challenges of neural networks combines NN with symbolic AI, or human-readable representations of search, logic, and problems. To successfully duplicate human intelligence, it's vital to translate the *procedural knowledge* or *implicit knowledge* (the skills and knowledge not readily accessible by conscious awareness) humans possess into an unequivocal form that uses symbols and rules. So far, the difficulties of developing symbolic AI have been unresolvable — but that status may soon change.

Computer scientists are working to eliminate these challenges. Leaders in the field of neural networks and AI are writing smarter, faster, more human algorithms every day. Engineers are driving improvements by using better hardware and cross-pollinating different hardware and software

X. THE FUTURE OF NEURAL NETWORKS

"We need to remember that artificial neural networks and deep learning are but one set of techniques for developing solutions to specific problems. Right now, they're the 'big thing,'" opines Richard Yonck, Founder and Lead Futurist of Intelligent Future Consulting and author of Heart of the Machine: Our Future in a World of Artificial Emotional Intelligence.

He adds, "It's that old saying: 'When your only tool is a hammer, everything looks like a nail.' Except everything isn't a nail, and deep learning doesn't work for all problems. There are all sorts of developments to come in the next couple of decades that may provide better solutions: one-shot learning, contextual natural language processing, emotion engines, common sense engines, and artificial creativity."

Here are some likely future developments in neural network technologies:

1) *Fuzzy Logic Integration:* Fuzzy logic recognizes more than simple true and false values — it takes into account concepts that are relative, like somewhat, sometimes, and usually. Fuzzy logic and neural networks are integrated for uses as diverse as screening job applicants, auto-engineering, building crane control, and monitoring glaucoma. Fuzzy logic will be an essential feature in future neural network applications.
2) *Pulsed Neural Networks:* Recently, neurobiological experiment data has clarified that mammalian biological neural networks connect and communicate through pulsing and use the timing of pulses to transmit information and perform computations. This recognition has accelerated significant research, including theoretical analyses, model development, neurobiological modeling, and hardware deployment, all aimed at making computing even more similar to the way our brains function.
3) *Specialized Hardware:* There's currently a development explosion to create the hardware that will speed and ultimately lower the price of neural networks, machine learning, and deep learning. Established companies and startups are racing to develop improved chips and graphic processing units, but the real news is the fast development of neural network processing units (NNPUs) and other AI specific hardware, collectively referred to as *neurosynaptic architectures*. Neurosynaptic chips are fundamental to the progress of AI because they function more like a biological brain than the core of a traditional computer. With its Brain Power technology, IBM has been a leader in the development of neurosynaptic chips. Unlike standard chips, which run continuously, Brain Power's chips are event-driven and operate on an as-needed basis. The technology integrates memory, computation, and communication.
4) *Improvement of Existing Technologies:* Enabled by new software and hardware as well as by current neural network technologies and the increased computing power of neurosynaptic architectures, neural networks have only begun to show what they can do. The myriad business applications of faster, cheaper, and more human-like problem-solving and improved training methods are highly lucrative.
5) *Robotics:* There have been countless predictions about robots that will be able to feel like us, see like us, and make prognostications about the world around them. These prophecies even include some dystopian versions of that future, from the *Terminator* film series to *Blade Runner* and *Westworld*. However, futurist Yonck says that we still have a very long way to go before robots replace us: "While these robots are learning in a limited way, it's a pretty far leap to say they're 'thinking.' There are so many things that have to happen before these systems can truly think in a fluid, non-brittle way. One of the critical factors I bring up in my book is the ability to establish and act on self-determined values in real-time, which we humans do thousands of times a day. Without this, these systems will fail every time conditions fall outside a predefined domain."

Mind-melding between human and artificial brains, according to Yonck, is in our future: "I think artificial intelligence, artificial neural networks, and deep learning will eventually play a far more active role in retraining our brains, particularly as brain-computer interfaces (BCIs) become more prevalent and widely used. Deep learning will be essential for learning to read and interpret an individual brain's language, and it will be used to optimize a different aspect of thought — focus, analysis, introspection. Eventually, this may be the path to IA (intelligence augmentation), a form of blended intelligence we'll see around the middle of this century."

XI. RESOURCES ON NEURAL NETWORKS

The brave new world of neural networks can be hard to understand and is constantly changing, so take advantage of these resources to stay abreast of the latest developments.

Neural network associations sponsor conferences, publish papers and periodicals, and post the latest discoveries about theory and applications. Below is a list of some of the major NN associations and how they describe their organizational goals:

1) *The International Neural Network Society (INNS):* The organization is for "individuals interested in a theoretical and computational understanding of the brain and applying that knowledge to develop new and more effective forms of machine intelligence."
2) *IEEE Computational Intelligence Society (IEEE CIS):* This is a professional society of the Institute of Electrical and Electronics Engineers (IEEE) who focus on "the theory, design, application, and development of biologically and linguistically motivated computational paradigms that emphasize the neural networks, connectionist systems, genetic algorithms, evolutionary programming, fuzzy systems, and hybrid intelligent systems in which these paradigms are contained."
3) *European Neural Network Society (ENNS):* This is an "association of scientists, engineers, students, and others seeking to learn about and advance our understanding of the modeling of behavioral and brain processes, develop neural algorithms, and apply neural modeling concepts to problems relevant in many different domains."

4) *International Institute for Forecasters (IIF):* This organization is "dedicated to developing and furthering the generation, distribution, and use of knowledge on forecasting."

Most of the titles provided below have been published within the last two years. We've also included a few classics of the discipline:

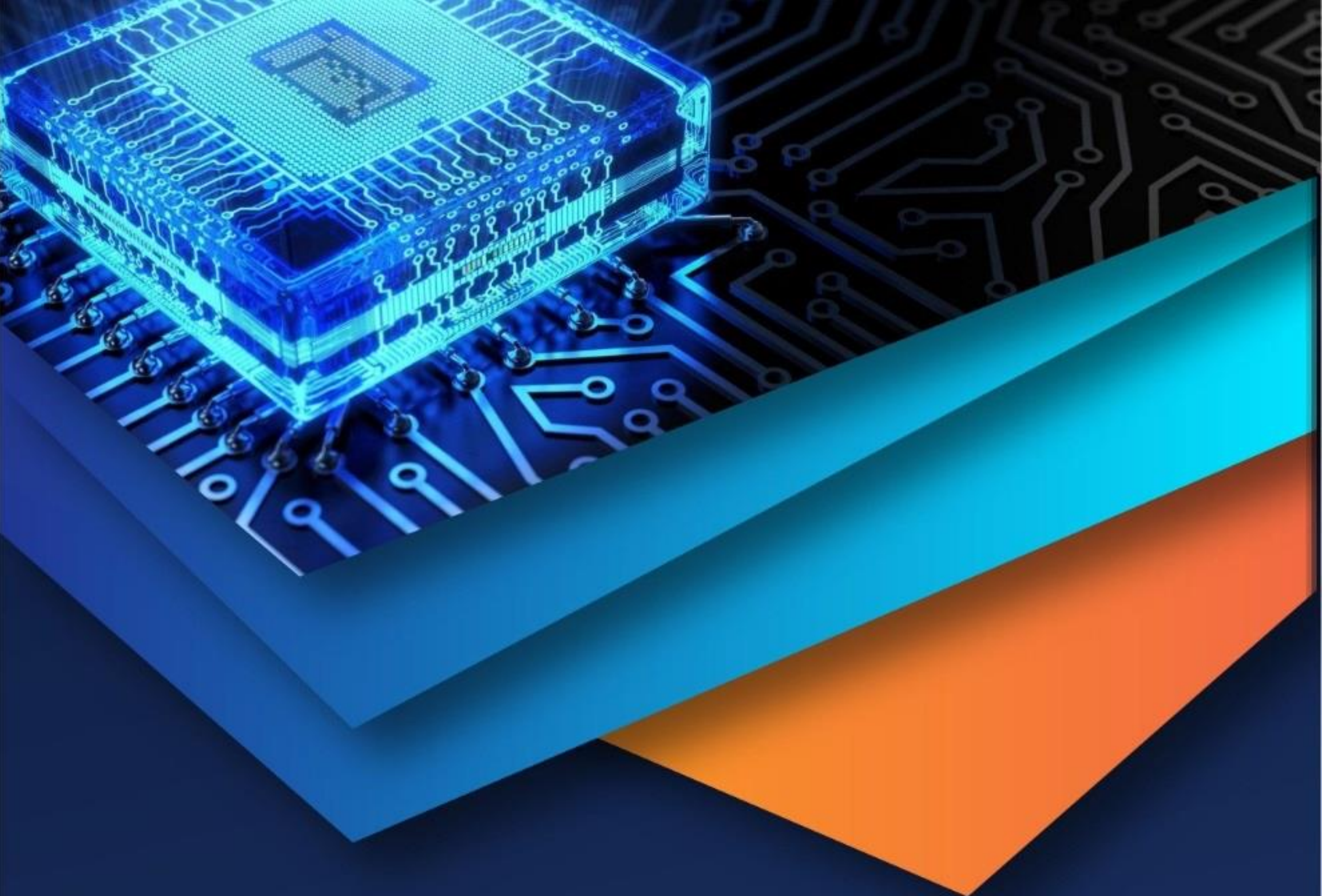
a) Aggarwal, Charu C. *Neural Networks and Deep Learning: A Textbook*. New York City: Springer International Publishing, 2018.
b) Goldberg, Yoav. *Neural Network Methods for Natural Language Processing (Synthesis Lectures on Human Language Technologies)*. Williston: Morgan & Claypool Publishers, 2017.
c) Hagan, Martin T., Demuth, Howard B., and Beale, Mark H. *Neural Network Design (2nd Edition)*. Martin Hagan, 2014.
d) Hassoun, Mohamad. *Fundamentals of Artificial Neural Networks*. Cambridge: The MIT Press | A Bradford Book, 2013.
e) Haykin, Simon O. *Neural Networks and Learning Machines (3rd Edition)*. Chennai: Pearson India, 2008.
f) Heaton, Jeff. *Introduction to the Math of Neural Networks*. Heaton Research, Inc., 2012.
g) Taylor, Michael. *Make Your Own Neural Network: An In-Depth Visual Introduction for Beginners*. Independently Published, 2017.

The world of neural networks has its own language. Here are some resources to expand your technical vocabulary and understanding of the field:

- *ESA Neural Network Glossary:* A compilation of neural networking terms from the European Space Agencies' Earthnet Online site
- *Medium Neural Network Glossary:* A frequently updated list of the latest terminology from the tech writing source site, *Medium*
- *Sky mind A.I. Wiki Glossary:* A frequently updated compendium of clearly defined terms concerning neural networks and deep artificial networks

REFERENCES

[1] Aleksander, I. 1980. Whatever happened to cybernetics? Technical Report N/S/103, Department of Electrical Engineering, Brunel University.
[2] Aleksander, I. & R.C.Albrow 1968. Microcircuit learning nets: some tests with handwritten numerals. Electronics Letters 4, 406–7.
[3] Aleksander, I. & H.Mamdani 1968. Microcircuit learning nets: improved recognition by means of pattern feedback. Electronics Letters 4, 425–6.
[4] Aleksander, I. & T.J.Stonham 1979. Guide to pattern recognition using random-access memories. Computers and Digital Techniques 2, 29–40.
[5] Aleksander, I., W.V.Thomas, P.A.Bowden 1984. WISARD: a radical step forward in image recognition. Sensor Review 4, 120–24.
[6] Amit, D.J. 1989. Modelling brain function: the world of attractor neural networks. Cambridge: Cambridge University Press.
[7] Amit, D.J. & H.Gutfreund 1985. Spin-glass models of neural networks. Physical Review A 32, 1007–18. Anderson, A. & E.Rosenfeld (eds) 1988. Neurocomputing: foundations of research . Cambridge, MA: MIT Press.
[8] Anderson, J.A. 1972. A simple neural network generating an interactive memory. Mathematical Biosciences 14, 197–220.
[9] Austin, J. 1987a. ADAM: A distributed associative memory for scene analysis. In 1st IEEE International Conference on Neural Networks, vol. IV, 285–92, San Diego.
[10] Austin, J. 1987b. The designs and application of associative memories for scene analysis. PhD thesis, Department of Electrical Engineering, Brunel University.
[11] Baba, N. 1989. A new approach for finding the global minimum of error function of neural networks. Neural Networks 2, 367–73.
[12] Banquet, J.P. & S.Grossberg 1987. Probing cognitive processes through the structure of event related potentials during learning: an experimental and theoretical analysis. Applied Optics 26, 4931–46.
[13] Barto, A.G. 1985. Learning by statistical cooperation of self-interested neuron-like computing elements. Human Neurobiology 4, 229–56.
[14] Barto, A.G. 1992. Reinforcement learning and adaptive. In Handbook of intelligent



10.22214/IJRASET

45.98

IMPACT FACTOR: 7.129

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY