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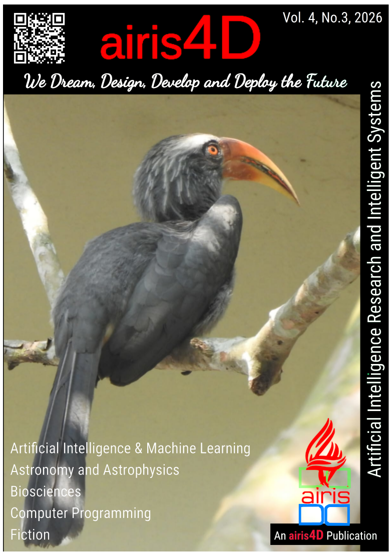

Cover page

"Kakka Vezhambal" is another name for the Malabar Grey Hornbill (Ocyceros griseus), a bird endemic to the Western Ghats . Commonly found in Kerala's evergreen and moist deciduous forests, it is known for its loud, cackling calls that are considered a characteristic sound of the region's wilderness . Recognizable by its brownish-grey plumage and yellow-orange bill, it primarily feeds on fruits like figs and plays a vital role in the forest ecosystem as a seed disperser . Photograph taken by Geetha Paul from airis4D campus.

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Editorial

by Fr Dr Abraham Mulamoottil

airis4D, Vol.4, No.3, 2026

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We are delighted to announce that airis4D Journal will feature a new monthly column titled Vijnanam—the Sanskrit word for knowledge—beginning in the May 2026 issue. The column will be authored by Prof. K. Babu Joseph, former Vice-Chancellor of Cochin University of Science and Technology (CUSAT) and currently an advisor to this journal. A distinguished physicist and accomplished writer, Prof. Joseph has published extensively on popular science, philosophy, and poetry in both English and Malayalam. Vijnanam will primarily explore themes in science, though it will occasionally venture into other disciplines, offering readers a rich and thoughtful perspective shaped by his multifaceted intellectual pursuits. We warmly welcome Prof. Babu Joseph to this regular feature and look forward to his valuable contributions.

This edition starts with "The Power of Small Visual Language Models," by Dr. Arun Aniyan, who argues that the future of artificial intelligence lies not in massive, resource-intensive systems but in their compact, efficient counterparts known as Small Visual Language Models (SVLMs). Aniyan explains that SVLMs achieve their efficiency through a significantly reduced parameter count and specialized training techniques like knowledge distillation, where a smaller "student" model learns from a larger "teacher" model's nuanced understanding. This streamlined design enables faster response times, lower energy consumption, reduced costs, and most importantly, allows these models to run directly on edge devices such as smartphones and smart cameras. By enabling this on-device intelligence, SVLMs enhance data privacy while powering practical applications across accessibility tools, manufacturing quality control, retail management, and contextual smart home systems, ultimately representing what Aniyan describes as a crucial step toward embedding ubiquitous, personal AI into everyday technology.

In "Introduction to Neuromorphic Computing- Part II," author Dr. Blesson George explores how brain-inspired computing offers an energy-efficient alternative to traditional systems by mimicking the neural and synaptic structures of the human brain. Aniyan explains that, unlike conventional computers, which suffer from the Von Neumann bottleneck and high power consumption, neuromorphic systems use event-driven Spiking Neural Networks (SNNs) and specialized chips like IBM's TrueNorth and Intel's Loihi to perform parallel, real-time processing with remarkable efficiency. The article highlights how these systems integrate memory and computation to enable low-power applications in robotics, edge AI, and adaptive sensing, while also acknowledging ongoing challenges such as the lack of standard programming frameworks and the difficulty of training SNNs. Ultimately, Aniyan positions neuromorphic computing as a promising paradigm shift toward intelligent systems that can learn continuously and operate with minimal energy consumption.

In "Plasma Physics- Magnetosphere & Ionosphere," Abishek P S examines how Earth's magnetic field creates a dynamic plasma environment that shields the planet while continuously exchanging energy and particles with the upper atmosphere. The article explains that the magnetosphere, formed by Earth's internal dynamo and shaped by the solar wind, traps charged particles in radiation belts and funnels them toward the poles to create auroras, while the ionosphere acts as both a source of plasma—supplying ions like oxygen and hydrogen upward—and a sink where precipitating particles deposit energy. Abishek details the coupling mechanisms that link these regions, including field-aligned currents that act as electrical pathways, Alfvén waves that transfer energy along magnetic field lines, and the pressure cooker effect that drives heavy ions into space during geomagnetic storms. The author emphasizes that this interconnected system serves as a natural plasma laboratory where scientists can study universal processes like turbulence, instabilities, and nonlinear coupling through direct satellite measurements, offering insights that extend from space weather forecasting to understanding astrophysical phenomena across the universe.

Aromal P provides in ”X-ray Astronomy: Theory” a comprehensive overview of the primary cosmic sources that emit X-rays and the physical mechanisms responsible for their radiation. The article explains that X-ray emission across the universe arises from extreme environments where matter is heated to millions of degrees or particles are accelerated to relativistic speeds. Stellar coronae, like our Sun's outer atmosphere, produce X-rays through magnetic reconnection and thermal bremsstrahlung, while supernova remnants generate both thermal emission from shock-heated gas and non-thermal synchrotron radiation from pulsar-accelerated electrons. X-ray binaries, the brightest sources in our galaxy, involve neutron stars or black holes accreting matter from companion stars, producing X-rays through disk viscosity, surface impact, and inverse Compton scattering. The author also describes isolated neutron stars cooling from formation or powered by magnetic field decay in magnetars, active galactic nuclei where supermassive black holes generate X-rays via coronal inverse Compton scattering, and galaxy clusters where the intracluster medium emits thermal bremsstrahlung from gravitational heating. Aromal, whose research focuses on thermonuclear X-ray bursts on neutron stars, presents these diverse sources as a testament to the universal processes of accretion, magnetic reconnection, and shock heating that make X-ray astronomy a powerful window into the most energetic phenomena in the cosmos.

In ”Giant Molecular Clouds: Structure, Evolution, and Their Role in Star Formation”, Sindhu G provides a comprehensive overview of the complex, multi-scale processes that transform cold interstellar gas into nuclear-burning stars. The article explains that star formation occurs almost exclusively within giant molecular clouds, where dense cores become gravitationally unstable when thermal pressure, turbulence, and magnetic fields can no longer support them against collapse—a condition quantified by the Jeans criterion. As collapse proceeds, conservation of angular momentum leads to the formation of circumstellar accretion disks that regulate material flow onto the central protostar, while magneto-centrifugal forces launch bipolar jets and outflows that remove excess angular momentum and provide feedback into the surrounding medium. Sindhu describes how protostars evolve through embedded phases, powered by gravitational contraction rather than fusion, before emerging as pre-main-sequence objects like T Tauri stars that gradually contract until hydrogen ignition marks their arrival on the zero-age main sequence. The author emphasizes that formation timescales vary dramatically with mass—from millions of years for Sun-like stars to less than a hundred thousand years for massive stars—and highlights how modern infrared and sub-millimetre observations from facilities like JWST continue to refine our understanding of these fundamental processes that shape galaxies and set the stage for planet formation.

Linn Abraham explores in ”Deep Learning: A Review,” the ttransition from Mchine Learning to Deep Learning. The article explains that while traditional interpretability tools like Integrated Gradients were designed for CNN architectures, transformer models offer a more natural approach by leveraging their built-in attention mechanisms. Abraham demonstrates how monkey patching—dynamically modifying code at runtime—allows researchers to replace standard attention blocks with patched versions without retraining the model, while PyTorch hooks enable the capture of attention matrices and their gradients during forward and backward passes. By registering hooks before and after the softmax operation in attention layers, the AGCAM method stores attention values and computes gradients through backpropagation, then combines these across layers and normalizes them with sigmoid activation to produce class activation maps that highlight which image regions influenced the model's decisions. This approach provides an intuitive visualization tool for understanding ViT behavior, with applications ranging from model debugging to building trust in AI systems used in fields like medical imaging or, as in the author's own work, solar flare prediction and galaxy classification.

Aengela Grace Jacob explores in ”Kombucha: 'The Symbiotic Elixir' – A Comprehensive View on its Bioprocessing,” the microbial science behind the popular fermented tea beverage, revealing how a simple mixture of sweetened tea transforms into a complex probiotic drink through the action of a SCOBY (Symbiotic Culture of Bacteria and Yeast). The article explains that this rubbery, cellulose-based disc serves as the living engine of fermentation, housing a diverse community of Acetic Acid Bacteria that produce acetic acid and build the SCOBY's physical structure, yeasts like Saccharomyces that convert sugar to ethanol and carbon dioxide, and Lactic Acid Bacteria that contribute sour flavors and probiotic properties. Jacob details the two-phase fermentation process—an initial aerobic stage where oxygen enables acid production, followed by anaerobic bottle conditioning that creates natural carbonation—and describes how enzymes like invertase break down sucrose into fermentable sugars. The author emphasizes kombucha's scientifically-backed benefits for gut health, including its ability to restore balanced gut flora through probiotic diversity, suppress harmful pathogens with organic acids, and increase the bioavailability of anti-inflammatory tea polyphenols, positioning this ancient elixir as a modern testament to the power of microbial symbiosis in promoting human wellness.

In ”The Genomic Landscape of Major Depressive Disorder,” Geetha Paul explores how modern genetic research has fundamentally transformed our understanding of depression from a single-gene disorder to a complex polygenic trait influenced by thousands of common genetic variations called single nucleotide polymorphisms (SNPs). The article explains that while individual SNPs exert only negligible effects on depression risk, their cumulative impact—measured through Polygenic Risk Scores (PRS)—can identify individuals with up to five times greater susceptibility to MDD before clinical symptoms ever manifest, enabling preemptive monitoring and personalized interventions. Paul highlights how SNP analysis helps resolve the diagnostic heterogeneity of depression by revealing distinct biological subtypes, with some patients carrying variants concentrated in serotonin pathways while others show genetic burdens in inflammatory genes like IL-6. The author also examines critical pharmacogenomic applications, detailing how specific polymorphisms such as the BDNF Val66Met variant, which impairs neural plasticity, and the SLC6A4 5-HTTLPR polymorphism, which influences serotonin transporter expression, can predict antidepressant response and guide treatment decisions. This molecular approach, Paul argues, moves psychiatry beyond the traditional one-size-fits-all model toward a more precise, stratified framework where genetic biomarkers bridge the gap between subjective symptom reporting and objective biological data.

Finally, Dr. Ajay Vibhute presents in ”From Telescope to Data Product” a comprehensive exploration of how computational methods have evolved from manual calculations and mechanical aids to become an indispensable instrument in modern astronomy, fundamentally transforming how scientists observe, analyze, and understand the cosmos. The article traces the historical progression from logarithmic tables and punched-card mainframes like the IBM 704 to sophisticated software pipelines that now process terabytes of data from surveys such as Hipparcos and the Sloan Digital Sky Survey, highlighting that computation functions not merely as a tool but as a virtual scientific instrument that actively shapes raw measurements into meaningful discoveries through algorithms for image deconvolution, source extraction, and statistical modeling. Dr. Vibhute explains that astronomical data presents unique challenges—massive volumes, inherent noise from multiple sources, instrumental response functions like point-spread functions, and multi-dimensional structure across spatial, temporal, and spectral domains—requiring specialized techniques and careful pipeline design that balances algorithmic sophistication with computational feasibility. The author emphasizes that astronomical computing encompasses the entire knowledge lifecycle from data acquisition and calibration through reduction, analysis, simulation of phenomena like galaxy formation, advanced visualization, and petabyte-scale archiving, all while remaining constrained by physical instrument limitations and the stochastic nature of photons. As data volumes continue to grow, Dr. Vibhute concludes that robust, transparent computational methods will become increasingly crucial, cementing computation's role as the essential bridge connecting raw observations to our fundamental understanding of the universe.

News Desk

Vijnanam by Prof Babu Joseph, former VC, CUSAT

airis4D has the pleasure of announcing a monthly column, titled Vijnanam, which in Sanskrit, means knowledge. It will be handled by Prof. K. Babu Joseph, formerly of CUSAT, and currently, an advisor to this journal. He is a physicist and a writer of popular science, philosophy and poetry in English and Malayalam.The series will be focussed on science, but occasionally, address other disciplines as well. The first contribution will appear in the May 2026 issue.

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Part I

Artificial Intelligence and Machine Learning

The Power of Small Visual Language Models

by Arun Aniyan

AIRIS4D, VOL.4, NO.3, 2026

www.airis4d.com

1.1 Introduction

Artificial Intelligence (AI) is rapidly transforming every sector of the world, and at the forefront of this evolution are models with the remarkable capability to process and understand both textual and visual information. These sophisticated systems are broadly categorized as Visual Language Models (VLMs). While the public imagination is often captured by immense, resource-intensive models that boast staggering performance metrics, a quieter, yet profoundly significant, technological shift is underway. This shift centers on their leaner, more efficient cousins: Small Visual Language Models (SVLMs).

The rise of SVLMs represents a critical inflection point in the AI landscape. They are designed to achieve high performance with a fraction of the parameters, computational power, and memory footprint required by their massive predecessors. This focus on efficiency makes them ideal for deployment in environments where resources are constrained, such as mobile devices, edge computing systems, and integrated hardware solutions.

This detailed exploration will delve into the core of the AI revolution driven by these compact systems. We will meticulously define the technical architecture and operational mechanisms of Small Visual Language Models, scrutinize the compelling reasons behind their growing importance—ranging from cost reduction and energy efficiency to improved privacy and real-time inference—and analyze the transformative impact they are having on the design and functionality of everyday technology.

1.2 What is a Visual Language Model (VLM)?

To understand a small VLM, we first need to grasp the concept of a regular VLM.

Imagine a machine that can look at a picture and simultaneously read a description of it, then use that combined understanding to answer questions or generate new text. This is the essence of a Visual Language Model. It is a type of AI that has been trained on a massive dataset of images paired with descriptive text (like captions, articles, or transcripts).

VLMs have two main ”brains” working together:

A Vision Encoder: This part processes the image, recognizing objects, shapes, colors, and spatial relationships. It turns the visual information into a numerical code the computer can understand.

A Language Decoder: This part handles the text, understanding grammar, meaning, and context. It’s often a powerful language model, similar to the ones used in smart assistants or translation tools.

The magic happens when these two parts learn to communicate, creating a unified understanding of ”what is seen” and ”what is said.”

1.3 The ’Small’ in Small Visual Language Models (SVLMs)

When we refer to Small Visual Language Models (SVLMs), the descriptor ”small” is fundamentally tied to the model’s size and its computational requirements. Unlike their larger, often monolithic counterparts, SVLMs are characterized by a significantly reduced number of parameters. This decreased parameter count directly translates into a smaller memory footprint, making these models substantially more accessible for deployment on edge devices, mobile platforms, and resource-constrained environments where large-scale GPU clusters are unavailable or impractical.

The minimized computational requirements are a critical advantage. This involves lower demands for processing power (FLOPs) during both the training and, crucially, the inference phases. A smaller model is faster to train, reducing the associated energy consumption and monetary cost, democratizing the development of multimodal AI. Furthermore, their lower inference latency and energy expenditure allow for real-time processing of visual and textual data locally, unlocking new applications in areas like augmented reality, robotics, and instantaneous on-device image analysis without needing constant cloud connectivity. Therefore, "small" is not a compromise on capability but a strategic design choice focused on efficiency, accessibility, and real-world deployability.

1.3.1 Model Size (Parameters)

Every AI model, regardless of its specific application—whether it's a sophisticated Large Language Model (LLM) or a specialized Small Visual Language Model (SVLM)—is fundamentally built upon an enormous number of adjustable settings referred to as parameters. These parameters are the core, tangible components that define the model's structure and capabilities.

Think of parameters as the accumulated knowledge, memories, and intricate connections that reside within the AI's artificial brain. During the training process, the AI is fed vast amounts of data (text, images, code, etc.). As it processes this data, it constantly adjusts the values of these billions of parameters. These adjustments are the process through which the model learns to identify patterns, understand context, generate coherent text, or recognize objects in an image.

Essentially, the greater the number of parameters, the more potential capacity the model has to learn complex relationships, store nuanced information, and perform diverse tasks. It is the precise configuration of these parameters—the delicate balance of their numerical values—that allows an AI to successfully execute its designed function.

SVLMs contain significantly fewer parameters than their massive counterparts. This reduction is intentional and offers profound advantages.

1.4 Efficiency and Speed

Smaller models require less computing power, which leads to several practical benefits:

- **Faster Response Times (Latency):** Because there are fewer calculations to perform, an SVLM can process an image and generate a response much quicker. This is crucial for real-time applications like autonomous driving or instant camera translations.
- **Reduced Energy Consumption:** Less processing power translates directly to less energy usage. This is vital for sustainability and for running AI on battery-powered devices.

Lower Cost: Training and deploying smaller models is vastly cheaper than deploying large models, making the technology accessible to a wider range of businesses and developers.

1.5 How SVLMs Work: The Training Secret

SVLMs don't just shrink the large models; they are often trained using specialized techniques to maximize their performance despite their size. One of the most effective and widely adopted strategies for creating powerful, yet resource-efficient, Small Visual Language Models (SVLMs) is a technique called knowledge distillation. This process is a revolutionary training paradigm that fundamentally shifts how smaller models acquire complex capabilities, moving away from brute-force training toward targeted, efficient knowledge transfer.

Model Type	Typical Parameter Count	Computational Needs	Primary Use Case
VLM	Billions (e.g., 50B+)	Requires massive, specialized data centers	Cutting-edge research, complex creative tasks
SVLM	Millions to low billions (e.g., 1B to 10B)	Can run on modern mobile devices or standard computers	Edge computing, specific enterprise applications

Table 1.1: Table showing comparison between VLMs and SVLMs

Table 1.1 shows the comparison of a typical VLM vs SVLM.

Knowledge distillation leverages a two-model system, often conceptualized using a 'teacher' and 'student' analogy:

1. **The 'Teacher' Model (VLM):**
   - This is typically a massive, state-of-the-art Large Visual Language Model (LVLM).
   - It is characterized by billions of parameters, trained on enormous and diverse datasets of raw images and text pairs over extensive computational resources.
   - The teacher model's 'knowledge' isn't just its final answer, but the nuanced *logic*, *intermediate representations*, and *soft probability distributions* it generates across various tasks (e.g., classifying an object as "90% cat, 10% dog" rather than just "cat"). This depth of understanding forms the core curriculum for the student.
2. **The 'Student' Model (SVLM):**
   - This is the small, target SVLM—the model designed for deployment on edge devices, mobile applications, or in environments with strict computational and memory constraints.
   - It possesses a significantly smaller architecture with far fewer parameters, which inherently makes it faster and more memory-efficient during inference.
3. **The Distillation Process (Efficient Knowledge Transfer):**
   - Instead of the traditional, laborious training approach where the SVLM is trained from scratch on vast, raw datasets, the SVLM is trained under the direct tutelage of the larger teacher model.
   - The core goal of distillation is to train the student to **mimic the decisions, sophisticated internal representations, and complex knowledge** encoded within the larger teacher model. The student is primarily guided by the teacher's *outputs* (the 'distilled' knowledge) rather than just the raw *labels* of the original data.
   - This is accomplished by utilizing a specialized **distillation loss function**. This function penalizes the student model when its predictions deviate from the teacher model's *soft targets* (i.e., its predicted probability distributions) for a given input. By aligning its internal workings with the teacher's nuanced outputs, the student effectively learns the 'wisdom' of the master.
   - It learns the **shortcuts**, the **most important conceptual features**, and the **efficient decision-making pathways** that the teacher model already took immense computational effort to figure out.

This highly optimized and focused training approach allows the SVLM to retain a surprising, and often near-equivalent, amount of the teacher model's high-level capability and performance across a range of visual-language tasks. Critically, it achieves this without the burden of the teacher's massive size, enabling the deployment of highly capable AI in resource-limited settings and accelerating the pace of the AI revolution on edge devices.

1.6 Why Small Models are the Future

For most real-world applications, large models are overkill. SVLMs are perfectly suited for deployment outside of huge data centers—a concept known as Edge Computing.

1.6.1 On-Device Intelligence

This is perhaps the biggest advantage. An SVLM can be entirely installed and run on a local device (the "edge"), such as:

- **Smartphones:** Enabling immediate, private image analysis and captioning without needing to send data to the cloud.
- **Smart Cameras:** Allowing a security camera to identify a package delivery in real-time, even if the internet connection is slow or unavailable.

Wearable Devices: Providing instant information, like identifying a foreign plant or translating a menu sign through smart glasses.

1.6.2 Enhanced Data Privacy

When the AI model runs directly on your device, your images and data never have to leave it to be processed. This ”on-device processing” significantly enhances user privacy and is becoming a major selling point for consumer electronics.

1.7 Real-World Applications of Small Visual Language Models

The efficiency and local nature of SVLMs open the door to countless practical uses:

1.7.1 Accessibility and Assistance

SVLMs are powerful tools for accessibility. For instance, a small model running on a person’s phone could:

- **Describe Environments:** For people with visual impairments, an SVLM can process a live camera feed and verbally describe the scene: ”You are standing next to a park bench; a dog is running toward a red ball.”
- **Read Complex Documents:** Instantly translate and summarize documents like utility bills or complex medication instructions by simply pointing a camera at them.

1.7.2 Manufacturing and Quality Control

In a factory setting, SVLMs can be deployed on a cheap, rugged computer to monitor production lines:

Defect Detection: A camera feed can be analyzed in real-time to spot tiny imperfections in a product, such as a scratch on a screen or a misaligned component. Since the model is small, it can make decisions instantly without causing bottlenecks.

1.7.3 Retail and Inventory Management

SVLMs are streamlining retail operations:

- **Stock Monitoring:** Cameras in a grocery store can use an SVLM to continually check shelves, instantly recognizing when a product is low and notifying staff for restocking.
- **Self-Checkout Verification:** Ensuring customers are scanning the correct items by visually confirming the item against its description.

1.7.4 Smart Home Devices

Future smart home hubs will rely on SVLMs for complex, local intelligence:

Contextual Understanding: Not just recognizing a person, but understanding context. For example, recognizing that a child has spilled a cup of milk and generating an alert for assistance.

1.8 Conclusion

Small Visual Language Models represent a crucial step toward ubiquitous AI. They address the practical limitations of massive models—cost, speed, and privacy—by providing highly capable intelligence in a compact, efficient package. As AI continues to evolve, it’s not always the biggest models that will win, but the smart, swift, and highly accessible SVLMs that will embed intelligence into the very fabric of our everyday devices, making the technology truly personal and powerful.

About the Author

Dr.Arun Aniyan is leading the R&D for Artificial intelligence at DeepAlert Ltd,UK. He comes from an academic background and has experience in designing machine learning products for different domains. His major interest is knowledge representation and computer vision.

Introduction to Neuromorphic Computing-Part II

by Blesson George

AIRIS4D, VOL.4, NO.3, 2026

www.airis4d.com

2.1 Introduction

Traditional computing systems have enabled remarkable technological progress. However, modern applications such as artificial intelligence, robotics, and real-time sensing require systems that are not only powerful but also energy efficient and adaptive. Conventional computers consume large amounts of energy when running complex AI models, which motivates researchers to explore alternative computing paradigms.

The human brain performs learning, perception, and decision-making using very little power. Neuromorphic computing attempts to imitate these biological principles to create more efficient intelligent systems.

2.2 Basic Idea of Neuromorphic Computing

The human brain consists of neurons connected through synapses. Neurons communicate using short electrical pulses called spikes. Learning occurs when the strength of synaptic connections changes over time.

Neuromorphic computing tries to reproduce this mechanism using electronic circuits. Artificial neurons process signals, and artificial synapses store connection strengths. Unlike traditional computers that continuously process data, neuromorphic systems are event-driven and become active only when input events occur.

This approach enables highly parallel computation and improved energy efficiency.

2.3 Why Neuromorphic Computing is Important

The growing interest in neuromorphic computing comes from several limitations of conventional computing.

2.3.1 Energy Consumption

Modern AI systems require large computational resources and high power usage. In contrast, the human brain operates at approximately 20 W while performing complex tasks. Neuromorphic systems aim to achieve similar efficiency through spike-based computation.

2.3.2 Von Neumann Bottleneck

In conventional computers, memory and processing units are physically separated. Constant data transfer between them creates delays and energy loss. Neuromorphic architectures combine memory and computation, reducing this bottleneck.

2.3.3 Real-Time Intelligence

Applications such as robotics and edge devices require fast responses and local decision-making. Neuromorphic systems support real-time processing due to their parallel and event-driven operation.

2.4 Spiking Neural Networks and Simple Neuron Model

Spiking Neural Networks (SNNs) are commonly used in neuromorphic computing because they closely resemble biological neural systems.

A simple model used to describe neuron behavior is the *Leaky Integrate-and-Fire (LIF)* model.

$$\tau \frac{dV(t)}{dt} = -V(t) + RI(t) \tag{2.1}$$

Here,

- $V(t)$ is the membrane potential,
- $I(t)$ is the input current,
- R represents membrane resistance,
- τ is the membrane time constant.

When the membrane potential reaches a threshold value V_{th}, the neuron generates a spike and the potential is reset. This model captures the essential firing behavior of biological neurons and forms the foundation of many neuromorphic systems.

2.5 Neuromorphic Chips

Neuromorphic chips are specialized processors designed to implement brain-inspired computation directly in hardware. Instead of executing instructions sequentially, these chips contain large numbers of artificial neurons and synapses that operate in parallel.

2.5.1 Working Principle

The basic operation of a neuromorphic chip includes:

1. Receiving input signals,
2. Integrating signals within neurons,
3. Generating spikes when thresholds are reached,
4. Transmitting spikes to connected neurons,
5. Updating synaptic strengths during learning.

Because computation occurs only when spikes are present, these chips consume much less energy compared to conventional processors.

2.5.2 Examples of Neuromorphic Chips

IBM TrueNorth is one of the earliest large-scale neuromorphic chips, containing around one million artificial neurons. It demonstrates extremely low power consumption and large-scale parallelism.

Intel Loihi is another important neuromorphic processor that supports on-chip learning. It allows adaptive behavior and real-time learning, making it useful for research in robotics and intelligent systems.

2.6 Difference from Conventional Computing

Neuromorphic computing differs fundamentally from traditional computing methods.

- Traditional computers use clock-driven operation, while neuromorphic systems are event-driven.
- Memory and processing are separate in conventional systems but integrated in neuromorphic architectures.
- Conventional AI simulates neural behavior in software, whereas neuromorphic systems implement it directly in hardware.
- Neuromorphic systems provide low-power and parallel processing.

These differences make neuromorphic computing attractive for future intelligent systems.

2.7 Applications

Neuromorphic computing has potential applications in several areas:

- Robotics and autonomous systems
- Speech and image recognition
- Edge AI and Internet of Things (IoT)
- Brain–machine interfaces
- Adaptive sensing and control systems

In many of these applications, fast response and low energy consumption are critical requirements.

2.8 Challenges

Despite its potential, neuromorphic computing still faces challenges:

- Lack of standard programming frameworks
- Difficulty in training spiking neural networks
- Hardware design complexity
- Limited large-scale commercial adoption

Research continues to address these challenges and improve usability.

2.9 Future Scope

Neuromorphic chips may play an important role in next-generation artificial intelligence. Future systems could combine conventional AI methods with neuromorphic hardware to achieve both accuracy and efficiency.

As research progresses, neuromorphic computing may enable intelligent systems that learn continuously, adapt to their environment, and operate with extremely low power.

2.10 Conclusion

Neuromorphic computing represents a shift toward brain-inspired computation. By using spike-based processing and highly parallel architectures, it offers an energy-efficient alternative to conventional computing. Neuromorphic chips demonstrate how these ideas can be implemented in hardware, opening new possibilities for robotics, AI, and intelligent devices. Although still in the early stages of development, this field has strong potential to shape the future of computing.

About the Author

Dr. Blesson George presently serves as an Assistant Professor of Physics at CMS College Kottayam, Kerala. His research pursuits encompass the development of machine learning algorithms, along with the utilization of machine learning techniques across diverse domains.

Deep Learning: A Review

by Linn Abraham

AIRIS4D, VOL.4, NO.3, 2026

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3.1 Introduction

In this series we attempt a review of deep learning. We start with defining machine learning and distinguishing it from existing methods. Then we learn about the early techniques in machine and about a special kind of ensemble learning technique as a case study. We follow this by learning about one of the most important algorithms in classical machine learning called the Perceptron. We end the review by discussing how Multi-Layer Perceptrons have led to the primitive forms of today's modern deep learning architectures.

3.2 What is Machine Learning?

We usually use the term Machine Learning in the context of referring to a class of computer algorithms or programs. If so, we need to ask ourselves the following question — What differentiates machine learning algorithms or programs from those that existed before. There exists a plethora of mathematical and statistical techniques from before the time Machine Learning became popular. Take for example the familiar least-squares fitting method. To answer this, I use two well-known quotes in the domain of machine learning or artificial intelligence.

- "Machine learning is the subfield of computer science that gives computers the ability to learn without being explicitly programmed." — Arthur Samuel.
- "A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E". — Tom M. Mitchell.

Combining both the ideas, we see that in comparison to algorithms which try to solve a problem using first principles or domain knowledge, machine learning algorithms rely more on the data (or instances) that we have may already have access to.

Another key differences is the idea of generalization to unseen data. This is where one first encounters the idea of splitting data into the three sets, namely training, validation and testing.

In machine learning, the objective is not merely to minimize error on the observed dataset, but to minimize error on *unseen data* drawn from the same underlying distribution. Formally, while classical fitting procedures often minimize the empirical risk

$$\hat{R}(f) = \frac{1}{n}\sum_{i=1}^{n} \ell\big(f(x_i), y_i\big),$$

machine learning is fundamentally concerned with minimizing the expected risk

$$R(f) = \mathbb{E}_{(x,y)\sim\mathcal{D}}\left[\ell\big(f(x), y\big)\right],$$

where $\mathcal{D}$ denotes the (unknown) data-generating distribution.

Because $\mathcal{D}$ is inaccessible in practice, machine learning algorithms must rely on finite samples to approximate this objective. This concern with generalization leads naturally to one of the defining methodological practices in machine learning: splitting available data into separate subsets, commonly referred to as *training*, *validation*, and *testing* sets. The training set is used to fit model parameters, the validation set to tune hyperparameters or select among models, and the test set to provide an unbiased estimate of generalization performance.

In this sense, machine learning can be viewed as an intersection of computer science, statistics, and optimization, with a distinctive focus on scalable algorithms, empirical evaluation, and predictive accuracy. The field is less concerned with discovering closed-form solutions derived from domain assumptions, and more concerned with building systems that adapt as data grows and improves performance through experience.

This perspective provides the foundation for the techniques discussed in the remainder of this chapter, from early "classical" machine learning methods to modern deep learning models.

3.3 Classical Machine Learning Techniques

Early machine learning research focused on a class of methods that are now commonly referred to as *classical* or *shallow* machine learning techniques. These methods typically rely on explicitly designed feature representations and relatively simple model architectures, in contrast to modern deep learning approaches that learn hierarchical representations automatically from raw data.

Some of the most influential classical machine learning techniques include support vector machines, decision trees, naive Bayes classifiers, and ensemble methods such as boosting and bagging. Despite their diversity, these techniques share a common goal: learning a function that generalizes well from observed examples to unseen data.

3.3.1 Gradient Boosting and XGBoost

Gradient Boosting generalizes the boosting framework underlying AdaBoost by framing the learning process as an optimization problem in function space. Rather than explicitly adjusting instance weights, Gradient Boosting sequentially fits weak learners to the negative gradient of a specified loss function, allowing greater flexibility in loss design and regularization compared to AdaBoost. While AdaBoost is commonly implemented using decision stumps, Gradient Boosting typically employs shallow decision trees with controlled depth, which can capture feature interactions.

Extensions such as XGBoost further enhance Gradient Boosting through an optimized and scalable implementation. XGBoost incorporates second-order gradient information, sparsity-aware tree construction, and approximate split-finding strategies, enabling efficient training on large and sparse datasets.

3.3.2 The Perceptron

The perceptron occupies a central place in the history of machine learning, serving both as one of the earliest learning algorithms and as the conceptual foundation for modern neural networks.Introduced in the late 1950s, the perceptron was among the first models capable of learning directly from data through an iterative update rule, rather than relying on fixed, hand-crafted decision rules.

At its core, the perceptron is a binary linear classifier. Given an input vector $x \in \mathbb{R}^d$, the model computes a weighted sum of the inputs and applies a threshold to produce an output:

$$y = \operatorname{sign}(w^\top x + b),$$

where $w \in \mathbb{R}^d$ is a vector of learnable weights and $b \in \mathbb{R}$ is a bias term. This formulation makes explicit the perceptron's role as a linear decision function: the model partitions the input space using a hyperplane defined by the parameters w and b.

What distinguishes the perceptron from earlier linear models is not its functional form, but its *learning rule*. Given a labeled training example (x_i, y_i) with $y_i \in \{-1, +1\}$, the perceptron updates its parameters only when it makes a mistake. The update rule can be written as

$$w \leftarrow w + \eta y_i x_i, \qquad b \leftarrow b + \eta y_i,$$

where $\eta > 0$ is the learning rate. This simple rule embodies the idea of learning from experience: the model adjusts its parameters incrementally in response to errors, improving performance over time.

Nevertheless, the perceptron remains critically important as a conceptual building block. By stacking multiple perceptrons and introducing nonlinear activation functions, one obtains multi-layer perceptrons (MLPs), which are capable of representing highly complex functions. In this sense, modern deep learning models can be viewed as extensions of the basic perceptron idea, augmented with depth, nonlinearity, and large-scale optimization techniques.

The perceptron thus serves as a bridge between classical machine learning and deep learning. It retains the interpretability and simplicity of early models while introducing the core mechanisms—parameterized functions and data-driven learning—that underpin contemporary neural network architectures.

3.4 Deep Learning

A direct extension of the perceptron is the *multi-layer perceptron* (MLP), which consists of multiple layers of neurons arranged in a feedforward architecture. Each layer applies an affine transformation followed by a nonlinear activation function. For an MLP with L layers, the forward computation can be written recursively as

$$h^{(0)} = x$$

and

$$h^{(l)} = \sigma\left(W^{(l)} h^{(l-1)} + b^{(l)}\right), \quad l = 1, \ldots, L,$$

where $W^{(l)}$ and $b^{(l)}$ denote the weights and biases of layer l, and $\sigma(\cdot)$ is a nonlinear activation function such as the sigmoid, hyperbolic tangent, or rectified linear unit.

The introduction of nonlinear activation functions is essential. In the absence of nonlinearity, the composition of multiple linear layers would reduce to a single linear transformation, offering no additional expressive power beyond that of a single-layer model. Nonlinearity enables deep networks to represent complex functions and capture intricate structure in data.

Training deep neural networks involves adjusting their parameters to minimize a loss function that quantifies the discrepancy between predictions and ground-truth labels. Given a dataset $\{(x_i, y_i)\}_{i=1}^{n}$ and a model f_θ parameterized by θ, the learning objective is typically written as

$$\min_{\theta} \frac{1}{n} \sum_{i=1}^{n} \ell\left(f_\theta(x_i), y_i\right),$$

where $\ell(\cdot, \cdot)$ denotes an appropriate loss function, such as mean squared error for regression or cross-entropy loss for classification.

The optimization of this objective is made feasible by the *backpropagation algorithm*, which efficiently computes gradients of the loss with respect to all model parameters using repeated applications of the chain rule. These gradients are then used by gradient-based optimization methods, such as stochastic gradient descent and its variants, to iteratively update the parameters.

A defining characteristic of deep learning is its ability to perform *representation learning*. Rather than relying on manually engineered features, deep models automatically learn representations that become increasingly abstract across successive layers. Lower layers typically capture simple patterns, while higher layers encode more complex and task-specific features.

Depth plays a central role in this process. From a theoretical perspective, deep architectures can represent certain classes of functions more efficiently than shallow ones. From a practical standpoint, depth allows models to reuse and recombine intermediate representations, improving both expressiveness and generalization.

Despite their success, deep learning models introduce new challenges. They often require large datasets, substantial computational resources, and careful regularization to avoid overfitting. Techniques such as dropout, weight decay, and batch normalization are commonly employed to stabilize training and improve generalization performance.

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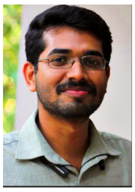
About the Author



Linn Abraham is a researcher in Physics, specializing in A.I. applications to astronomy. He is currently involved in the development of CNN based Computer Vision tools for prediction of solar flares from images of the Sun, morphological classifications of galaxies from optical images surveys and radio galaxy source extraction from radio observations.

Part II

Astronomy and Astrophysics

Plasma Physics- Magnetosphere & Ionosphere

by Abishek P S

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www.airis4d.com

1.1 Introduction

The magnetosphere is a vast, invisible region surrounding Earth where its magnetic field dominates and interacts with charged particles from the Sun. It is generated by the planet's internal dynamo, the movement of molten, electrically conducting material in the outer core of the planet which produces a magnetic field resembling that of a bar magnet near the surface. However, this field is distorted farther out by the solar wind, a continuous stream of charged particles emitted by the Sun. On the side facing the Sun, the magnetosphere is compressed, while on the opposite side it stretches into a long tail called the magnetotail. Its boundaries include the bow shock, where the solar wind first encounters resistance, and the magnetopause, where the pressure of the solar wind balances Earth's magnetic field [1].

This protective bubble plays a crucial role in shielding Earth from harmful solar and cosmic radiation, preventing atmospheric erosion, and making the planet habitable. It also traps charged particles in radiation belts and funnels some toward the poles, producing auroras. The magnetosphere is highly dynamic, constantly reshaped by solar activity, and during strong solar storms it can be compressed, leading to geomagnetic disturbances that affect satellites, power grids, and communications. Other planets also have magnetospheres, though their strength and structure vary[2]. Jupiter's magnetosphere is the largest in the solar system, while Mars largely lacks one, contributing to its thin atmosphere. In a broader cosmic perspective, magnetospheres are fundamental structures that govern how celestial bodies interact with their space environment, acting as shields and mediators between planetary systems and the energetic universe around them.

1.2 The Magnetosphere as a Plasma Environment

The magnetosphere, when viewed as a plasma environment, is far more than just a magnetic bubble around Earth. It is a dynamic system filled with charged particles from both the solar wind and Earth's ionosphere. These plasma populations interact with the magnetic field in complex ways, giving rise to processes that drive space weather and influence conditions on Earth. One important plasma population comes from the solar wind. Protons and electrons from the Sun continuously stream toward Earth, and some of them penetrate the magnetosphere through a process called magnetic reconnection at the magnetopause. This entry point allows solar particles to mix with Earth's magnetic environment, fuelling storms and disturbances. Alongside these, heavy ions such as oxygen (O^+) and helium (He^+) originating from Earth's ionosphere are lifted upward by electric fields and waves. Once energized, they contribute to the overall plasma density and dynamics of the magnetosphere, especially during geomagnetic storms[3,4].

Magnetic reconnection is a key process in this environment. It occurs when oppositely directed magnetic field lines break and reconnect, releasing stored magnetic energy and converting it into particle kinetic energy. This drives large-scale convection of plasma throughout the magnetosphere and triggers substorms, which are sudden disturbances that can intensify auroras and disrupt communication systems. Reconnection is often described as the "engine" of magnetospheric dynamics because it powers so many of the system's changes[3].

Alfvén waves are another crucial mechanism. These are oscillations that travel along magnetic field lines, carrying energy and field-aligned currents between the magnetosphere and ionosphere. They act as conduits for energy transfer, enabling the coupling of Earth's upper atmosphere with space. Through these waves, disturbances in the magnetosphere can directly influence ionospheric currents and auroral activity, making them a vital link in the chain of magnetospheric processes[5].

Ring current is a large-scale plasma structure formed by energized ions circulating around Earth. During geomagnetic storms, these ions build up and create a current that encircles the planet. The ring current contributes significantly to geomagnetic disturbances by altering Earth's magnetic field, which can weaken the overall field strength temporarily[6]. This weakening is one of the hallmarks of geomagnetic storms and has practical consequences, such as affecting satellite operations and navigation systems. Magnetic reconnection, Alfvén waves, and ring current formation are central to its behaviour, making the magnetosphere a fascinating and complex plasma laboratory in space.

1.3 The Ionosphere as a Plasma Source and Sink

The ionosphere is a dense plasma layer of Earth's upper atmosphere, created when solar ultraviolet (UV) and X-ray radiation ionizes neutral atoms and molecules. This region acts both as a source of plasma for the magnetosphere and as a sink where magnetospheric particles deposit their energy. Its dual role makes it a critical part of the coupled Earth–space environment.

As a plasma source, the ionosphere provides heavy ions such as oxygen (O^+), which are accelerated upward by electric fields, wave–particle interactions, and heating processes. These ions escape into the magnetosphere, where they contribute to plasma populations in the plasma sheet and ring current. During geomagnetic storms, this outflow intensifies, and O^+ ions become a dominant component, altering the dynamics of the magnetosphere. In addition to heavy ions, lighter ions like hydrogen (H^+) and helium (He^+) continuously flow outward in what is known as the polar wind. This steady stream of light ions represents a constant supply of plasma to the magnetosphere, even under quiet conditions.

As a plasma sink, the ionosphere absorbs energy and particles from the magnetosphere. Precipitating electrons and ions collide with neutral atoms in the upper atmosphere, producing auroras, the shimmering lights seen near polar regions. These collisions also enhance ionization in localized regions, modifying the conductivity of the ionosphere and influencing currents that flow between the magnetosphere and Earth. This feedback loop ensures that the ionosphere is not only a supplier of plasma but also a recipient of magnetospheric energy[7].

Plasma transport processes highlight the ionosphere's dynamic role. The polar wind represents a continuous, low-level outflow of light ions, maintaining a background plasma supply. In contrast, storm-time outflows are episodic and powerful, with enhanced O^+ fluxes dominating the plasma sheet and ring current during geomagnetic storms. These storm-driven outflows significantly reshape the magnetosphere, fuelling geomagnetic disturbances and contributing to the weakening of Earth's magnetic field during storms.

1.4 Coupling Mechanisms

Field-aligned currents (FACs) are one of the most important coupling mechanisms between the magnetosphere and ionosphere. These electric currents flow directly along magnetic field lines, linking the dynamics of the magnetosphere to the conductivity of the ionosphere. When solar wind and magnetospheric processes drive changes in the magnetic field, FACs carry those changes down into the ionosphere, where they influence ionospheric currents and heating[8]. In this way, FACs act as the "wires" of the system, ensuring that energy and momentum are transferred between space and Earth's upper atmosphere.

Auroral acceleration regions represent another key coupling process. In these regions, Alfvénic turbulence and parallel electric fields accelerate electrons downward along magnetic field lines. As these electrons collide with neutral atoms in the upper atmosphere, they produce the bright auroral arcs that we see near the poles[5]. The acceleration process is not uniform; instead, it creates structured, shimmering displays that reflect the turbulent nature of the plasma environment. These regions are therefore critical in transforming magnetospheric energy into visible auroral phenomena, while also enhancing ionization in the ionosphere.

The pressure cooker effect is a more subtle but equally important mechanism. Downward currents compress plasma at low altitudes, creating localized regions of high pressure. This compression energizes heavy ions such as O^+, driving them upward into the magnetosphere. In effect, the ionosphere acts like a plasma reservoir that can be "pumped" by magnetospheric currents. During geomagnetic storms, this effect becomes especially pronounced, with large fluxes of O^+ ions escaping upward to dominate the plasma sheet and ring current[6]. This upward transport of ions alters the composition and dynamics of the magnetosphere, feeding back into the larger system.

Together, these coupling mechanisms illustrate how the magnetosphere and ionosphere are not isolated systems but deeply interconnected. FACs provide the electrical pathways, auroral acceleration regions convert energy into light and ionization, and the pressure cooker effect drives plasma upward. Each process contributes to the continuous exchange of energy and particles, making Earth's near-space environment a highly dynamic and interactive plasma system.

1.5 Energy Flow

Solar wind energy enters Earth's magnetosphere primarily through magnetic reconnection at the dayside magnetopause. This process allows the solar wind's magnetic field to merge with Earth's, opening pathways for energy and plasma to flow into the magnetosphere. Once inside, this energy does not remain localized but is redistributed through several interconnected mechanisms that shape the dynamics of Earth's near-space environment[2].

One major redistribution process is magnetospheric convection, which refers to the large-scale circulation of plasma throughout the magnetosphere. Driven by reconnection, plasma flows from the dayside magnetopause into the magnetotail and then returns toward Earth[1]. This circulation pattern transports energy and particles across vast distances, fuelling substorms and setting the stage for auroral activity. Convection ensures that solar wind energy is spread throughout the magnetosphere rather than concentrated in one region.

Wave–particle interactions provide another pathway for energy redistribution. Waves such as Alfvén waves and whistler-mode waves propagate through the magnetosphere, transferring energy to charged particles. Alfvén waves, in particular, carry field-aligned currents that couple the magnetosphere to the ionosphere, enabling energy to flow downward. Whistler-mode waves can scatter energetic electrons, redistributing their energy and sometimes precipitating them into the atmosphere[5]. These interactions are essential for regulating particle populations and maintaining the dynamic balance of the magnetosphere.

Particle precipitation represents a direct way in which magnetospheric energy is deposited into Earth's atmosphere. Electrons accelerated along magnetic field lines collide with neutral atoms in the upper atmosphere, producing auroras. This process not only creates the spectacular light displays near the poles but also enhances ionization in the ionosphere, altering its conductivity and influencing global current systems. Through precipitation, magnetospheric energy is transformed into both visual phenomena and atmospheric changes.

1.6 Magnetosphere & Ionosphere in Research Perspective

Plasma physicists regard the magnetosphere–ionosphere system as a natural laboratory for studying universal plasma processes, because it exhibits many of the same behaviours seen in astrophysical environments across the universe. One of the most important aspects is turbulence. In the magnetosphere, plasma flows and magnetic reconnection events generate turbulent structures, where energy cascades from large scales down to smaller ones. This turbulence is similar to what occurs in solar corona plasmas, astrophysical jets, and even interstellar medium turbulence, making near-Earth space an accessible place to study these otherwise remote phenomena.

Instabilities are another key feature. The magnetosphere is full of plasma instabilities, such as the Kelvin–Helmholtz instability at the magnetopause, which develops when solar wind flows shear against Earth's magnetic boundary[9]. Other instabilities, like those in the plasma sheet, can trigger substorms and auroral activity. These processes mirror instabilities found in fusion devices and astrophysical disks, offering scientists a chance to test theories of how plasmas behave when disturbed.

Nonlinear coupling is also central to this system. The magnetosphere and ionosphere are tightly linked through field-aligned currents, wave–particle interactions, and feedback loops. Small changes in one region can lead to large-scale responses in the other, demonstrating nonlinear dynamics. This coupling is a microcosm of the complex interactions seen in larger astrophysical systems, such as star–planet interactions or accretion flows around black holes.

What makes near-Earth space especially valuable is the ability to obtain in situ measurements. Satellites and ground-based instruments can directly measure plasma density, temperature, particle fluxes, and wave spectra. These observations provide real-time data that allow scientists to test and refine theories of plasma circulation, turbulence, and energy transfer. Unlike distant astrophysical plasmas, which can only be observed indirectly through light or radiation, the magnetosphere–ionosphere system offers a hands-on testbed for plasma physics.

In essence, the magnetosphere–ionosphere system demonstrates turbulence, instabilities, and nonlinear coupling in ways that are universal to plasma environments across the cosmos. By studying it with direct measurements, plasma physicists gain insights that apply not only to Earth's space weather but also to the broader universe, from solar flares to galactic jets.

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About the Author

Abishek P S is a Research Scholar in the Department of Physics, Bharata Mata College (Autonomous) Thrikkakara, kochi. He pursues research in the field of Theoretical Plasma physics. His works mainly focus on the Nonlinear Wave Phenomenons in Space and Astrophysical Plasmas.

X-ray Astronomy: Theory

by Aromal P

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2.1 Introduction

In our previous article, we discussed the various sources of cosmic X-rays and the mechanisms that produce them. We will continue with a series exploring these different sources in detail. As the author specializes in X-ray binaries, we will begin with an in-depth look at their various classes before moving on to other topics.

As the name suggests, X-ray binaries are double-star systems that emit electromagnetic waves in the X-ray region. To put this in perspective, consider our own Sun. It is an average main-sequence star whose thermal emission peaks in the visible range, with a surface temperature of around 5,500 K. Producing thermal X-rays, however, requires temperatures of millions of Kelvin! It feels unbearably hot in summer, even though we are 8.3 light-minutes away from the Sun. So, imagine the intensity of an environment with temperatures reaching millions or even billions of Kelvin! X-ray binaries are home to these incredibly energetic phenomena.

What is the driving force behind this? Surprisingly, it is the weakest of all fundamental forces—gravity. This is the remarkable story of how gravity, the universe's most delicate force, gives rise to some of its most powerful and energetic displays.

2.2 X-ray Binaries

Gravity achieves this spectacular heating through a mechanism called accretion, the continuous flow of matter from a companion star into the deep gravitational well of a dense, compact object. Just as water releases energy as it plunges down a waterfall, the gas in these systems converts its enormous gravitational potential energy into intense heat and radiation as it falls.

To understand the math behind this sheer power, we can look at the fundamental formula for the luminosity (or power output), L, generated by this accretion:

$$L = GM\dot{M}/R. \tag{2.1}$$

In this equation, G represents the gravitational constant, M is the mass of the compact object, $\dot{M}$ is the mass accretion rate (how much matter falls per second), and R is the radius of the compact object. Notice that the radius R is in the denominator. Because compact objects are incredibly small, the denominator is minimal, making the resulting X-ray luminosity very large.

We can also approximate this power using Albert Einstein's famous equation for rest-mass energy, $E = mc^2$. The luminosity can be expressed as a fraction of the total energy the falling matter possesses: $L = \eta\dot{M}c^2$, where η represents the efficiency of the energy conversion ($\eta = GM/Rc^2$). For nuclear fusion the exact process that makes our Sun shine this efficiency is a mere 0.001 to 0.01 (that is only 0.1% to 1% of the mass is converted into energy). In contrast, the efficiency η for matter accreting onto a neutron star is roughly 0.1 (that is 10%), and for a black hole, it can reach an astonishing 0.42 (42%). This proves that gravitational accretion onto compact objects is the most efficient mechanism known in the universe for converting matter into energy, vastly outperforming nuclear reactions. Just a handful of matter can produce an X-ray luminosity 10,000 times greater than the total energy output of the Sun at all wavelengths.

What is at the core of these extreme systems that generate such a strong gravitational pull? The engines behind them are compact objects, which are the collapsed remnants of former stars, the ghost of a dead star. These remnants appear when a star dies. There are generally three forms of these objects, depending on the original mass of the dying star. It's important to outline these forms to provide a complete discussion of the topic.

2.2.1 White Dwarfs

When an average star, similar to our Sun, exhausts its nuclear fuel, its core can no longer generate the outward pressure needed to support its own weight. The core collapses until it is halted by the quantum resistance of crowded electrons, a phenomenon known as degenerate electron pressure. The resulting object is a white dwarf. A white dwarf packs roughly the mass of the Sun ($\sim 1\ M\odot$) into a sphere about the size of the Earth, which has a radius of approximately 10,000 kilometres. White dwarfs are strictly limited in weight and cannot exceed $1.44\ M\odot$, a boundary known as the Chandrasekhar limit. Systems with accreting white dwarfs are called cataclysmic variables. Because white dwarfs have a relatively large radius compared to other compact objects, their gravitational wells are shallower, making their accretion process much less luminous in X-rays.

2.2.2 Neutron Stars

When a much more massive star (greater than $10\ M\odot$) reaches the end of its life, its core collapses so violently that even electron pressure cannot stop the crush of gravity. In a fraction of a second, electrons and protons are squeezed together to form a fluid of neutrons. This triggers a catastrophic supernova explosion that blows away the outer star, leaving behind a neutron star. A neutron star is a bizarre state of matter; it compresses a mass equivalent to the Sun's into a sphere with a radius of just 10 to 15 kilometers, roughly the size of a small city. Its density is equal to that of an atomic nucleus, so dense that a chunk the size of a table spoon of matter would weigh more than the mass of earth. Because its radius R is so tiny, the accretion formula $L = GM\dot{M}/R$ dictates that in falling matter reaches immense velocities, heating up to tens of millions of degrees and radiating copious amounts of X-rays. Typical neutron stars have a mass of around $1.4\ M\odot$, with theoretical maximum limits near $3\ M\odot$.

2.2.3 Black Holes

For the most massive stars in the universe($> 25\ M\odot$), the core collapse is so profound that even the rigid pressure of compressed neutrons cannot halt the crushing force of gravity. The core collapses entirely upon itself, creating a black hole. A black hole is characterized by an event horizon—a boundary beyond which the gravitational pull is so intense that nothing, not even light, can escape. While black holes do not have a hard physical surface like a neutron star, we can still observe them as brilliant X-ray sources. The intense X-ray emission we see actually comes from the superheated accretion disk of matter swirling frantically just outside the event horizon before it crosses the boundary. Black holes are also of different sizes, and here we are discussing about stellar-mass black holes in X-ray binaries which typically have masses ranging from greater than $3\ M\odot$ up to about $15\ M\odot$.. Do not get confused with the supermassive black holes that used to be found in the center of the galaxies we will discuss about then in the upcoming articles.

As we have discussed about the compact object its a good time to discuss about the different classes of X-ray binaries usually called as XRBs. Based on the mass of the companion star we can classify the X-ray binaries into two as Low-mass X-ray binaries and High-mass X-ray binaries.

2.2.4 Low-mass X-ray Binaries

In an LMXB, the companion star supplying the fuel is an older, late-type star that is generally less massive than our own Sun, or even a tiny degenerate dwarf. Because these companion stars are much older and have long lifespans, LMXBs are typically found residing in regions populated by old stars, such as the central Galactic Bulge of the Milky Way and the dense, crowded cores of globular clusters.

The mass transfer mechanism in an LMXB relies on the evolutionary expansion of this small companion star. As the star ages, it pulls outward until it completely fills its gravitational boundary, a pear-shaped equipotential surface known as a Roche lobe. Once it fills this lobe, the star's outer gaseous layers physically spill over a gravitational saddle point between the two stars—called the inner Lagrangian point ($L1$) and fall toward the compact object. Because the two stars are orbiting each other, this transferred matter carries significant orbital angular momentum. Therefore, it cannot plummet straight down onto the compact object. Instead, it spirals inward to form a flat, superheated, rapidly spinning structure called an accretion disk. Internal friction and viscosity within this disk heat the gas to millions of degrees, producing the bright X-rays we observe before the matter makes its final plunge.

2.2.5 High-mass X-ray Binaries

In these systems, the companion star is a massive, young, early-type star (such as an O or B spectral type) that can weigh 10 times the mass of the Sun or more. Because these massive stars burn through their nuclear fuel rapidly and live very short, furious lives, HMXBs are typically found in the spiral arms of our galaxy, close to the stellar nurseries where they recently formed.

Unlike the older, smaller stars in LMXBs that gently spill their mass over a gravitational boundary, these massive hot stars naturally blow off a highly energetic stellar wind of gas similar to the solar storms observed in sun. This wind is driven outward by the intense pressure of the star's own ultraviolet radiation, and it carries off a huge amount of material in all directions. As the compact object orbits through this dense, outflowing hurricane of gas, its intense gravity acts like a cosmic vacuum cleaner. It captures a fraction of the passing gas in a process mathematically described as Bondi-Hoyle accretion. This wind-fed material falls onto the compact object, generating a powerful shock front and emitting X-rays as it crashes down. In some specific HMXBs, especially those containing rapidly spinning "Be" stars, the compact object travels on a highly elliptical orbit and periodically plunges through a dense equatorial disk of ejected material surrounding the massive star, causing bright, repeating transient outbursts of X-ray energy.

Is accretion the only process responsible for producing X-rays in X-ray binary systems? Is there something more? To answer this question, we need to discuss these systems in detail, which we will continue in the upcoming article.

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About the Author

Aromal P is a research scholar in Department of Astronomy, Astrophysics and Space Engineering (DAASE) in Indian Institute of Technology Indore. His research mainly focuses on studies of Thermonuclear X-ray Bursts on Neutron star surface and its interaction with the Accretion disk and Corona.

Giant Molecular Clouds: Structure, Evolution, and Their Role in Star Formation

by Sindhu G

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www.airis4d.com

3.1 Introduction

The space between stars in galaxies is not empty but filled with gas, dust, cosmic rays, and magnetic fields, collectively known as the interstellar medium (ISM). Among its various components, molecular clouds are the densest and coldest regions. Giant Molecular Clouds (GMCs) are the largest of these structures and serve as stellar nurseries where new stars and planetary systems are formed.

In spiral galaxies such as the Milky Way, GMCs are primarily located along spiral arms. These regions experience enhanced gas compression, which promotes the formation of molecular hydrogen. GMCs typically contain tens of thousands to several million times the mass of the Sun and extend over distances ranging from a few tens to a few hundred parsecs. Their extremely low temperatures, generally between 10 and 20 Kelvin, create ideal conditions for gravitational collapse and star formation.

3.2 Chemical Composition and Physical Characteristics

3.2.1 Molecular Content

The dominant component of GMCs is molecular hydrogen, which constitutes roughly three-quarters of their total mass. Helium accounts for most of the remaining mass, while heavier elements and dust grains contribute a small but important fraction.

Although molecular hydrogen is the most abundant molecule, it is difficult to observe directly because it does not emit radiation efficiently at low temperatures. Astronomers therefore use carbon monoxide as a tracer molecule. Emission from carbon monoxide allows researchers to estimate the amount of molecular hydrogen present within a cloud.

Dust grains play an essential role in molecular cloud chemistry. They shield molecules from destructive ultraviolet radiation and provide surfaces on which molecular hydrogen can form. In addition, dust grains emit infrared radiation, which helps regulate the thermal balance of the cloud.

3.2.2 Temperature and Density

GMCs are extremely cold compared to most astrophysical environments. Their temperatures typically range from 10 to 20 Kelvin. At such low temperatures, thermal motion of particles is weak, allowing gravity to influence the cloud's evolution more effectively.

The average particle density in a GMC is relatively modest compared to terrestrial standards, but it is significantly higher than in the surrounding ISM. Within these clouds, denser regions known as clumps and cores can reach much higher densities. These dense cores are the direct birthplaces of stars.

3.2.3 Mass and Size

GMCs are among the largest coherent structures in galaxies. Their masses range from ten thousand to several million solar masses. Despite their enormous mass, they remain gravitationally delicate structures due to their low temperatures and complex internal dynamics.

Observations show that many GMCs share similar surface densities, suggesting that common physical processes govern their formation and evolution.

3.3 Formation of Giant Molecular Clouds

The formation of GMCs is closely linked to large-scale galactic processes.

3.3.1 Spiral Density Waves

In spiral galaxies, large-scale density waves move through the galactic disk. As gas enters these regions, it becomes compressed. This compression increases density, allowing atomic hydrogen to transform into molecular hydrogen. Over time, these compressed regions grow into giant molecular clouds.

3.3.2 Gravitational Instabilities

If the gas density in a galactic disk becomes sufficiently high, gravitational forces can cause it to fragment into large molecular complexes. These instabilities help convert diffuse interstellar gas into dense molecular clouds.

3.3.3 Stellar Feedback and Cloud Collisions

Massive stars influence their surroundings through stellar winds and supernova explosions. These energetic events can sweep up surrounding gas into expanding shells. As these shells cool and accumulate material, they may fragment and form new molecular clouds. Additionally, collisions between smaller clouds can compress gas and contribute to GMC formation.

3.4 Internal Structure of GMCs

Modern observations reveal that GMCs are far from uniform. Instead, they exhibit a highly complex and hierarchical structure.

3.4.1 Filaments

Filamentary structures are commonly observed within molecular clouds. These elongated structures often extend for several parsecs and contain chains of dense cores. Filaments appear to be fundamental building blocks of molecular clouds and play a crucial role in star formation.

3.4.2 Clumps and Cores

Within filaments, material gathers into clumps and cores. Clumps are intermediate-scale dense regions that may form clusters of stars. Cores are smaller and denser regions that typically give rise to individual stars or small multiple systems.

The hierarchical organization of filaments, clumps, and cores reflects the combined influence of turbulence and gravity within the cloud.

3.5 Cloud Dynamics: Turbulence and Magnetic Fields

3.5.1 Turbulence

Observations show that gas motions within GMCs are highly turbulent and often supersonic. Turbulence serves two important roles. On large scales, it can support the cloud against complete gravitational collapse. On smaller scales, it creates localized density enhancements that promote star formation.

However, turbulence dissipates energy over time and must be continuously replenished. Large-scale galactic motions and feedback from young stars are likely sources of this energy.

3.5.2 Magnetic Fields

Magnetic fields are present throughout the interstellar medium and permeate GMCs. These fields can provide additional support against gravitational collapse. In some cases, magnetic forces influence the orientation of filaments and regulate how material flows within the cloud.

The balance between gravity, turbulence, and magnetic fields determines the efficiency and rate of star formation.

3.6 Star Formation in Giant Molecular Clouds

Star formation begins within dense cores when gravity overcomes internal support mechanisms. As a core collapses, material accumulates at the center, forming a protostar. Surrounding material may form an accretion disk, from which planets can eventually emerge.

Most stars form in clusters rather than in isolation. Massive GMCs can produce entire stellar associations containing hundreds or thousands of stars.

Despite their large mass, GMCs convert only a small fraction of their gas into stars. Radiation, stellar winds, and eventual supernova explosions from massive stars disperse the surrounding gas, limiting further star formation.

3.7 Lifetimes and Evolution

GMCs are not permanent structures. Their lifetimes are typically estimated to be between 10 and 30 million years. During this time, they evolve through several stages:

1. Formation from diffuse interstellar gas.
2. Growth and fragmentation into filaments and cores.
3. Active star formation.
4. Dispersal by stellar feedback.

The dispersal phase returns enriched material to the ISM, contributing to the next generation of molecular clouds.

3.8 Observational Techniques

Because GMCs are cold and dust-rich, they are primarily studied at radio, infrared, and submillimeter wavelengths.

Radio observations of carbon monoxide trace the distribution of molecular gas. Infrared observations reveal embedded young stellar objects and warm dust emission. Submillimeter telescopes provide high-resolution maps of dense cores and filaments.

Advances in observational facilities have significantly improved our understanding of molecular cloud structure and star formation processes.

3.9 Role in Galactic Evolution

GMCs regulate the star formation rate within galaxies. The continuous cycle of cloud formation, star birth, and cloud dispersal drives chemical enrichment and influences galactic structure.

Massive stars formed within GMCs eventually explode as supernovae, injecting energy and heavy elements into the ISM. This feedback process shapes the future evolution of galaxies.

3.10 Conclusion

Giant Molecular Clouds are fundamental components of galaxies and the principal sites of star formation. Their low temperatures, large masses, and complex internal structures create ideal environments for gravitational collapse and stellar birth. Although significant progress has been made in understanding their formation and evolution, ongoing research continues to refine our knowledge of these remarkable cosmic structures.

Understanding GMCs provides essential insight into the origin of stars, planetary systems, and the broader evolution of galaxies.

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About the Author

Sindhu G is a research scholar in the Department of Physics at St. Thomas College, Kozhencherry. She is doing research in Astronomy & Astrophysics, with her work primarily focusing on the classification of variable stars using different machine learning algorithms. She is also involved in period prediction for various types of variable stars—especially eclipsing binaries—and in the study of optical counterparts of X-ray binaries.

Part III

Biosciences

Kombucha: "The Symbiotic Elixir" A Comprehensive View on its Bioprocessing

by Aengela Grace Jacob

AIRIS4D, VOL.4, NO.3, 2026

www.airis4d.com

1.1 Introduction

Kombucha, often referred to as the *i*mmortal health elixir in ancient Chinese texts, is a fermented tea beverage that has exploded in popularity across the globe. Far more than just a trendy drink, Kombucha is a complex, living ecosystem captured in a bottle. In small-scale and home brewing, kombucha is typically made in glass jars topped with fabric. Black or green tea leaves are steeped in hot water with sugar, then removed. When the sweetened tea has cooled, it is mixed with a bit of kombucha from a previous batch to make the liquid more acidic. A gelatinous mat of symbiotic culture of bacteria and yeast (SCOBY) is then added, and the brew is covered with a tight-weave fabric or paper coffee filter and left to ferment at room temperature for 7–30 days. This article delves into the microbial composition, the remarkable symbiotic culture that creates it, the intricate fermentation process, and its powerful impact on human gut health.

Figure 1: Home made kombucha

Image Courtesy:https://www.healthygreenkitchen.com/how-to-make-kombucha-at-home/

1.2 SCOBY: The Heart of the Brew

The core of Kombucha is the SCOBY (Symbiotic Culture of Bacteria and Yeast). Visually, it is a thick, rubbery, beige disc. While often called a *K*ombucha mushroom, it is actually a dense structure of cellulose fibers created by bacteria. The living components of SCOBY can vary widely but generally include strains of Saccharomyces cerevisiae and other yeasts, as well as a number of bacteria, including *Gluconacetobacter xylinus*. Fresh or dehydrated SCOBY can be bought from suppliers, or a "mother" can be taken from a previous batch of kombucha. In the fermentation process, the alcohols produced by the yeasts are converted by the bacteria into organic acids. The final kombucha product contains vitamin C, vitamins B6 and B12, thiamin, acetic acid, and lactic acid, as well as small amounts of sugar and ethanol. The SCOBY acts as the living engine that transforms sweetened tea into an elixir, serving as both a fermenting agent and a protective seal for the liquid.

1.3 Microbial Contents: The Living Force

A single bottle of Kombucha is teeming with billions of microorganisms. While the exact

Figure 2: SCOBY

Image Courtesy:https://escarpmentlabs.com/blogs/resources/the-road-to-scoby

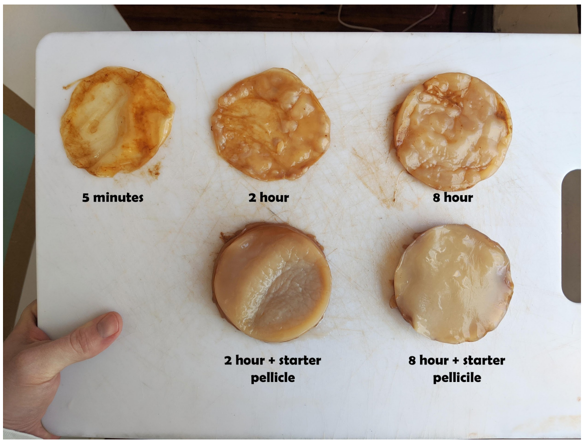

Figure 3: SCOBY GROWTH

Image Courtesy: https://www.reddit.com/r/Kombucha/comments/glo9ez/scoby_growth_experiment_varying_steep_times/

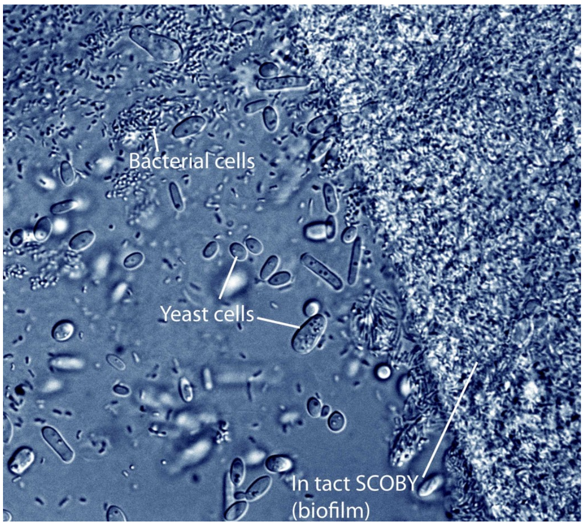

Figure 4: Magnification of Scoby at 400X by Benjamin Wolfe

Image Courtesy:https://microbialfoods.org/science-digested-microbial-diversity-kombucha/

microbiome varies, the core players include:

Acetic Acid Bacteria (AAB): These produce the defining acetic acid (vinegar) and build the SCOBY's physical structure.

Yeast: These convert sugar into ethanol and carbon dioxide (CO_2), providing the $f$uel for the bacteria.

Lactic Acid Bacteria (LAB): These contribute to the sour flavor and enhance the drink's probiotic properties.

1.4 The Fermentation Mechanism

The creation of Kombucha is a synchronized chemical dance consisting of two primary phases:

Phase 1: Primary Fermentation (Aerobic)

In an open container, yeast consumes sugar to produce ethanol. Simultaneously, the Acetic Acid Bacteria consume that ethanol and oxygen from the air to produce acetic acid and gluconic acid. This stage creates the tart flavor profile.

Phase 2: Secondary Fermentation (Anaerobic)

The liquid is bottled and sealed. Without oxygen, the yeast continues to ferment the remaining sugar, but the resulting CO_2 is trapped, creating natural carbonation.

The fermentation mechanism operates through a complex, synergistic interaction between various microorganisms.

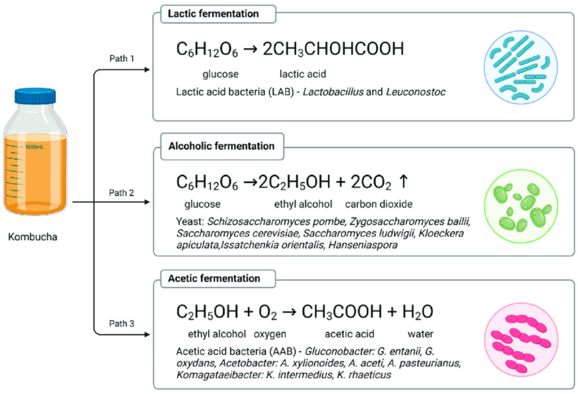

Figure 5: Fermentation Mechanism

: Image Courtesy:https://www.researchgate.net/figure/Types-of-fermentation-in-Kombucha-Created-with-BioRendercom_fig1_365463218

Initial Hydrolysis (Yeast): Yeast (such as Saccharomyces) produces the enzyme invertase, which breaks down sucrose into glucose and fructose. Secondly, alcoholic fermentation when Yeast metabolizes the glucose and fructose to produce ethanol and carbon dioxide (CO_2), contributing to the beverage's carbonation. Thirdly, Acidic fermentation Bacteria like Acetic acid bacteria (AAB, e.g., Acetobacter and Gluconobacter) and Lactic Acid Bacteria (LAB) consume the ethanol and sugars to produce acetic acid, lactic acid, and gluconic acid. Cellulose formation occurs when the AAB uses the glucose to synthesize a thick cellulose biofilm, which is the SCOBY pellicle, acting as a barrier and enabling oxygen exchange.

1.5 Major Benefits on Gut Health

The most scientifically backed benefits of Kombucha revolve around the gastrointestinal system which includes probiotic diversity as it restores natural balance to gut flora, aiding digestion and immune function. The probiotics (such as Lactobacillus and Bifidobacterium) can help restore balance to the microbiome by suppressing the growth of harmful bacteria. Fermented foods like kombucha are recommended to help re-establish healthy gut bacteria after a course of antibiotics disrupts the natural flora. Studies suggest that regular kombucha consumption may modulate the gut microbiota in ways that improve metabolic health, particularly in individuals with obesity, by encouraging beneficial bacteria like Akkermansiaceae. Organic acids like acetic and gluconic acids inhibit harmful pathogens and act as *p*ostbiotics to support the gut lining. It provides an antioxidant boost through fermentation as it increases the bioavailability of tea polyphenols, which combat inflammation in the digestive tract.

1.6 Conclusion

Kombucha is a testament to the power of microbial symbiosis. Through the collaborative effort of bacteria and yeast, a simple pot of sweet tea is transformed into a potent tool for human wellness. By providing a rich source of probiotics and antioxidants, it remains a timeless path toward internal balance.

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About the Author


Aengela Grace Jacob is Final Year Student of Bsc Biotechnology , Chemistry (BSc BtC) Dual Major at Christ University Central campus, Bangalore

The Genomic Landscape of Major Depressive Disorder

by Geetha Paul

airis4D, Vol.4, No.3, 2026

www.airis4d.com

2.1 Introduction

Major Depressive Disorder (MDD) is a globally prevalent psychiatric condition characterised by persistent low mood, anhedonia, and cognitive dysfunction. Despite decades of clinical study, the underlying aetiology of MDD remained largely elusive until the advent of the genomic era. Traditional views often sought a single depression gene, a silver bullet that could explain the condition's onset. However, modern genetic research, particularly large-scale Genome-Wide Association Studies (GWAS), has fundamentally dismantled this notion. We now understand MDD as a polygenic trait, meaning its genetic liability is distributed across thousands of common genetic variations, primarily single-nucleotide polymorphisms (SNPs).

A SNP represents a single letter change in the DNA sequence (e.g., a Cytosine replacing a Thymine). Individually, these SNPs exert a negligible effect on an individual's risk; when aggregated, they form a complex genetic architecture that accounts for roughly **10–15% of the total variance** in depression liability (SNP-based heritability). This polygenic nature explains the high degree of **heterogeneity** seen in clinics: because different combinations of thousands of SNPs can lead to a diagnosis, two patients may share the same label but possess entirely different biological drivers.

The role of SNPs in MDD detection is not about a binary yes/no diagnosis but about quantifying susceptibility and resolving the disorder's cryptic biological subtypes. Researchers utilise **Polygenic Risk Scores (PRS)** as a standardised quantitative metric. This score aggregates the weighted effects of thousands of **single-nucleotide polymorphisms (SNPs)** discovered via large-scale **Genome-Wide Association Studies (GWAS)**. By calculating this cumulative genetic burden, scientists can effectively stratify populations by risk level. This process identifies individuals with high latent vulnerability to **Major Depressive Disorder (MDD)**, even before clinical symptoms manifest. This molecular approach bridges the gap between subjective symptom reporting and objective biological data, paving the way for a more precise, stratified approach to mental health that moves away from a one-size-fits-all model toward **personalised psychiatry**.

2.2 Quantifying Genetic Liability via Polygenic Risk Scores (PRS)

Since no single gene causes depression, risk detection relies on the cumulative signal from thousands of SNPs. The **Polygenic Risk Score (PRS)** is the primary tool used to measure this. Recent studies have shown that individuals in the top 2.5% of the PRS distribution have a significantly higher risk (up to 5 times greater) of developing MDD than those with average scores. PRS can identify high-risk individuals before the first clinical episode, enabling preemptive monitoring and resilience-building interventions.

2.3 Resolving Diagnostic Heterogeneity

One of the most significant roles of SNPs is identifying cryptic subtypes of depression. While the DSM-5 lists symptoms, SNPs reveal the underlying biological pathways. Some patients carry SNPs concentrated in serotonin/dopamine pathways (e.g., SLC6A4, DRD2), while others show a high burden of SNPs in inflammatory genes (*IL-6*, *CRP*). Research shows that MDD shares a p-factor (a general genetic liability) with other disorders like Bipolar Disorder and Schizophrenia, which SNPs help untangle.

2.4 Pharmacogenomics and Treatment Response

SNPs are critical in detecting how a patient will respond to medication, a field known as pharmacogenomics. Variants in the **CYP2D6** and **CYP2C19** genes determine how quickly the liver metabolises antidepressants. Detection of Ultra-rapid or Poor metabolize r SNPs prevents toxicity and treatment failure. Variations in the *BDNF* (Brain-Derived Neurotrophic Factor) gene can predict the success of SSRIs, as they influence the brain's ability to physically adapt and heal during treatment.

Example 1: The ***BDNF*** Val66Met Polymorphism (rs6265)

The **Brain-Derived Neurotrophic Factor (BDNF)** gene encodes a protein that acts like fertilizer for the brain, helping neurons grow and form new connections (synapses).

The BDNF transcript comprises one of eight 5' untranslated exons (exon I-VIII) and the common 3' protein coding exon IX; B: Intracellular signalling after TrkB activation. Following BDNF binding, TrkB dimerisation and its phosphorylation at intracellular tyrosine residues occur. Then, the activated TrkB stimulates three main signalling pathways: (1) mitogen-activated protein kinase/extracellular signal-regulated kinase (MAPK/ERK); (2) phosphatidylinositol 3-kinase (PI3K); and (3) phospholipase Cγ (PLCγ)

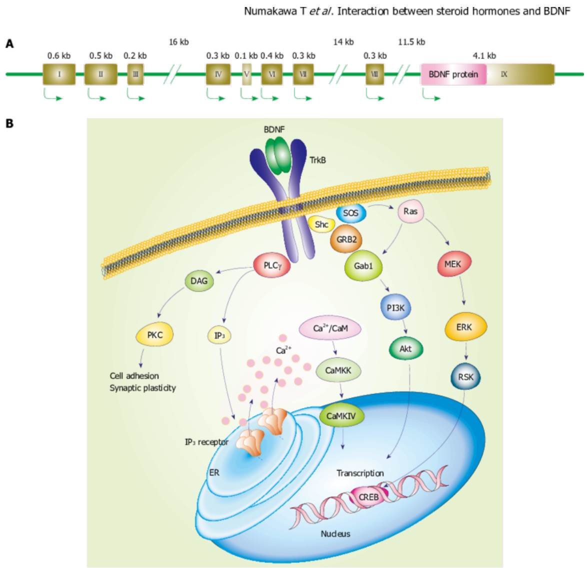

Figure 1: Brain-derived neurotrophic factor (BDNF) gene and stimulated intracellular signalling cascades after activation of tropomyosin-related kinase (Trk)B.

Image courtesy:https://tse3.mm.bing.net/th/id/OIP.Kk1ntIO-iez3fzmc93LTdAHaHS?pid=ImgDet&w=204&h=200&c=7&dpr=1.3&o=7&rm=3

pathways. The MAPK pathway, in which MAPK/ERK kinase (MEK) is involved, plays a role in neuronal differentiation and outgrowth. PI3K signalling promotes neuronal survival via Ras or GRB-associated binder 1 (Gab1). Following PLCγ activation, inositol-1,4,5-trisphosphate (IP3) and diacylglycerol (DAG) are both produced. DAG activates protein kinase C (PKC), which is important for regulating synaptic plasticity. Meanwhile, IP3 increases intracellular Ca 2+ concentration via IP3 receptors on the endoplasmic reticulum (ER), resulting in activation of Ca 2+ /calmodulin (CaM)-dependent protein kinase, including CaMKII, CaMKK, and CaMKI. These MAPK/ERK, PI3K, and PLCγ pathways can regulate gene transcription.

In the SNP, a single nucleotide switch causes the amino acid **Valine (Val)** to be replaced by **Methionine (Met)** at position 66. The Met variant impairs BDNF secretion. Research shows that individuals with the **Met allele** often have a smaller **hippocampus**, the brain region responsible for emotion regulation and memory.

Clinical Impact:

Detection of this SNP helps clinicians understand why some patients suffer from treatment-resistant depression. Because their brains have lower plasticity,

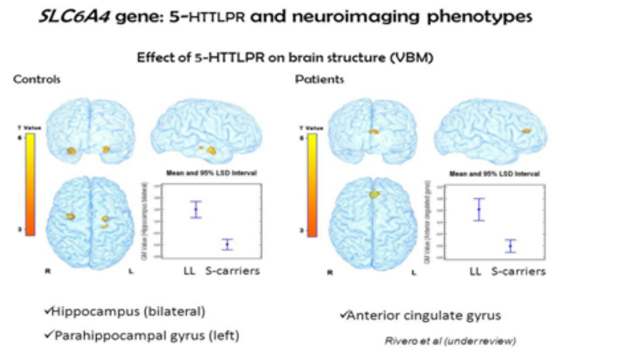

Figure 2: Schematic view of how the SLC6A4 and 5-HTTLPR genes effectiveness in different parts of the brain.

Image courtesy:https://medcraveonline.com/IJMBOA/assessment-of-genetic-mutations-by-the-genersquos-5-httlpr-and-slc6a4-and-scc6a4-in-the-human-depression.html

standard antidepressants may take longer to work or require supplemental therapies like Exercise or TMS (Transcranial Magnetic Stimulation), which naturally boost BDNF levels.

Example 2: The *SLC6A4* 5-HTTLPR Polymorphism

The *SLC6A4* 5-HTTLPR Polymorphism is perhaps the most famous example of a cryptic genetic marker in psychiatry. It involves the **Serotonin Transporter Gene**, which is the primary target for Selective Serotonin Reuptake Inhibitors (SSRI) antidepressants (like Prozac or Lexapro). Serotonin is the happiness hormone.

The SLC6A4 gene encodes the serotonin transporter, and its 5-HTTLPR polymorphism significantly influences serotonin reuptake, impacting mood regulation and responses to antidepressants.

The Variation: This is a functional polymorphism in the gene's promoter region, often categorised into **Short (S)** and **Long (L)** alleles.

The Mechanism: The **S allele** results in lower expression of the serotonin transporter. This makes the brain's emotional centre (the **amygdala**) hyper-reactive to stress.

Clinical Impact

Stress Sensitivity: People with the S allele are statistically more likely to develop MDD following a stressful life event (Gene-Environment Interaction).

SSRI Response: Studies suggest that individuals with the **L/L genotype** generally respond better and faster to SSRIs than those with the S allele, who may experience more side effects

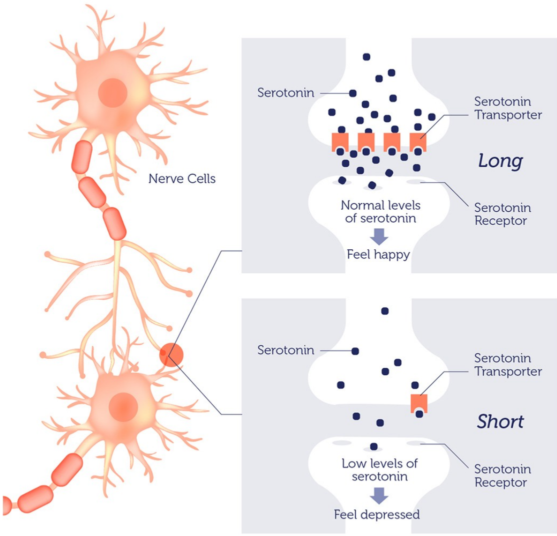

Figure 3: SLC6A4-5-HTTLPR. The SLC6A4 gene encodes the protein responsible for serotonin reuptake. The 5-HTTLPR polymorphism in the promoter region dictates expression levels: the short (S) allele reduces transcription, leading to lower transporter density on the presynaptic membrane compared to the long (L) allele. This mechanism is the primary target for SSRI antidepressants.

Image courtesy:https://genesight.com/white-papers/get-to-know-a-gene-slc6a4/

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About the Author

Geetha Paul is one of the directors of airis4D. She leads the Biosciences Division. Her research interests extends from Cell & Molecular Biology to Environmental Sciences, Odonatology, and Aquatic Biology.

Part IV

Computer Programming

From Telescope to Data Product

by Ajay Vibhute

AIRIS4D, VOL.4, NO.3, 2026

www.airis4d.com

1.1 From Telescope to Data Product

1.1.1 Raw Measurements vs Scientific Data

The journey from a telescope's detector to a usable scientific data product begins with raw measurements, which are simply numerical values—counts or voltages—recorded by the instrument. These values reflect the detector's response to incoming radiation rather than direct physical properties of celestial objects. A CCD pixel, for example, measures accumulated charge generated by photons, but that signal also includes contributions from background sky emission, electronic offsets, thermal noise, and occasional cosmic ray events. Raw measurements are further shaped by the instrument itself. The telescope's point-spread function spreads light from a single source over multiple pixels, and variations in pixel sensitivity introduce spatial inconsistencies. Detector nonlinearities and electronic effects can distort signals, particularly at high flux levels. As a result, the raw image is not a direct representation of the sky, but a convolution of the true scene with instrumental response, embedded within noise, figure 1. Because of this, raw data are not immediately interpretable in physical terms. Transforming them into scientifically meaningful data requires computational corrections such as bias subtraction, flat-fielding, background modeling, and calibration into standardized physical units. These steps convert instrument-dependent signals into quantities that can be reliably compared and scientifically analyzed, figure 2.

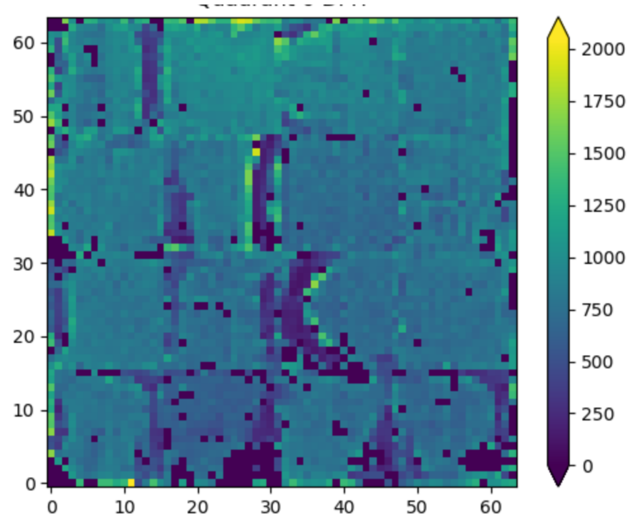

Figure 1: Recorded Raw image

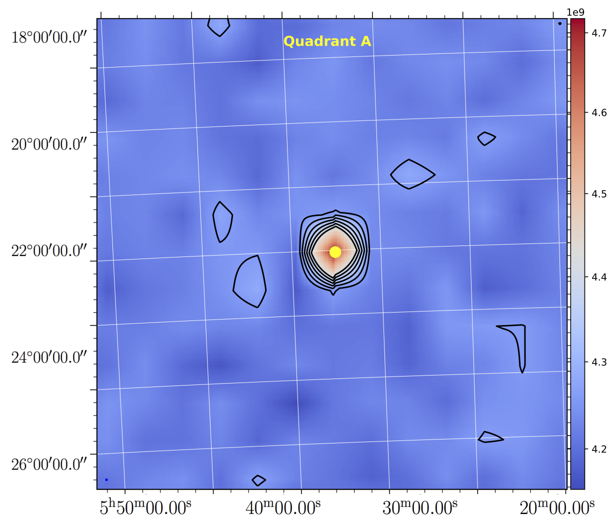

Figure 2: Reconstructed sky image

1.1.2 Data Acquisition and Instrument Effects

Data acquisition in astronomy is far from a passive recording process. Each measurement is shaped by the design of the telescope, the properties of the detectors, and the observing environment. The optical configuration determines angular resolution and light-gathering power, while alignment errors, mirror imperfections, or thermal expansion can subtly alter image quality. In ground-based observations, atmospheric turbulence blurs incoming light, producing time-varying distortions commonly referred to as seeing. Atmospheric extinction and sky background further modify the signal before it even reaches the detector. In space-based instruments, although the atmosphere is absent, other challenges arise, including cosmic ray impacts, thermal fluctuations, and small pointing instabilities of the spacecraft. Detectors themselves introduce additional complexities. Readout noise affects faint signals, pixel-to-pixel sensitivity variations create spatial non-uniformities, and charge diffusion can blur sharp features. Bright sources may saturate detector elements, leading to nonlinear responses or data loss in high-intensity regions. Even the timing of exposures and the stability of electronics influence the final measurement. Understanding these influences is essential because they fundamentally shape the raw data. Computational corrections applied later—such as deblurring, background subtraction, and calibration—depend on accurate models of these instrumental and environmental effects. In this way, data acquisition and computational processing are tightly interconnected stages of a single measurement process.

1.1.3 Calibration as a Computational Task

Calibration transforms raw measurements into quantitative, scientifically meaningful data by systematically correcting for instrumental and environmental effects. At its most basic level, this includes procedures such as bias subtraction to remove electronic offsets, dark current subtraction to account for thermally generated charge, and flat-fielding to correct for pixel-to-pixel sensitivity variations. These steps ensure that the recorded signal more accurately reflects incoming radiation rather than detector imperfections. In imaging, calibration may also involve modeling and subtracting background sky emission, while in spectroscopy it includes wavelength calibration using known spectral lines. Beyond these corrections, calibration extends to photometric and spectral transformations, converting detector counts into standardized physical units such as flux density, magnitude, or calibrated wavelength. This often requires reference observations of standard stars or laboratory calibration sources, enabling measurements from different instruments or observing runs to be directly compared. Astrometric calibration further aligns images with celestial coordinate systems, allowing precise positional measurements. In modern astronomy, calibration is primarily a computational process, embedded within automated pipelines that apply corrections consistently across thousands or millions of observations. Because calibration defines the quantitative scale of the data, even small inaccuracies can introduce systematic biases that propagate into derived parameters such as distances, masses, or luminosities. For this reason, calibration procedures must be rigorously validated, regularly updated, and carefully documented to ensure the reliability and reproducibility of scientific results.

1.1.4 Standard Data Products in Astronomy

Once calibrated, data can be transformed into standardized products suitable for analysis, distribution, and long-term archiving. These products include processed images, calibrated spectra, time-series light curves, and structured catalogs of detected sources. Each product is typically accompanied by extensive metadata describing observing conditions, calibration parameters, uncertainty estimates, and quality flags. This contextual information is essential, as it allows researchers to assess reliability, propagate uncertainties, and reproduce results. Standardization is critical because modern astronomy is inherently comparative and cumulative. Datasets from different instruments, observatories, or observing epochs must be interoperable to enable cross-matching, multiwavelength analysis, and large-scale statistical studies. Uniform data formats, coordinate systems, and calibration conventions make it possible to combine observations across surveys and to perform automated analyses on millions or billions of sources. In large-scale projects such as the Sloan Digital Sky Survey (SDSS) or Gaia, standardized data products form the backbone of scientific research, supporting investigations into stellar populations, galactic structure, dark matter distribution, and cosmology. Computational pipelines are central to the production of these products. From ingesting raw detector outputs to performing source detection, photometric measurement, and catalog assembly, pipelines ensure consistency and scalability. They also embed quality-control procedures that flag anomalies and track processing provenance. In this way, standardized data products represent not just processed observations, but carefully curated outputs of an integrated computational system designed to support reliable scientific discovery.

1.1.5 Sources of Systematic Error

Even after calibration and processing, systematic errors can affect data quality and interpretation in subtle but significant ways. Unlike random noise, which tends to average out over many measurements, systematic effects introduce consistent biases that can shift results in a particular direction. These errors may stem from instrumental limitations such as optical aberrations, imperfect flat-field corrections, detector nonlinearities, or long-term drift in sensitivity. Environmental factors—including variations in atmospheric transparency, scattered light, thermal instability, or imperfect background subtraction—can also leave residual signatures in the data. In addition, the data reduction algorithms themselves can introduce biases. Assumptions about noise distributions, source shapes, background levels, or model parametrizations may not hold uniformly across all observations. For example, an incorrect model of the point-spread function can distort photometric measurements, while oversimplified background modeling can artificially enhance or suppress faint sources. In large surveys, even small systematic biases can accumulate across millions of objects, leading to measurable distortions in statistical analyses. Systematic errors are particularly challenging because they can mimic or obscure genuine astrophysical signals, sometimes producing apparent trends or correlations that are not physically real. Detecting and mitigating these effects requires rigorous validation procedures, cross-comparisons with independent instruments or surveys, simulation-based testing, and careful uncertainty modeling. In modern astronomical computing, controlling systematic error is often as important as increasing statistical precision, and it remains one of the central challenges in producing reliable scientific results.

1.1.6 Concluding Remarks

The transformation from telescope to data product illustrates the central role of computation in modern astronomy. Every stage—from raw measurement to calibrated image or structured catalog—depends on algorithms that correct instrumental effects, model uncertainties, and extract meaningful signals from complex data. Scientific results therefore reflect not only the performance of the telescope, but also the assumptions and design of the computational pipeline. Understanding both the physical origins of measurements and the methods used to process them is essential for producing reliable and reproducible science. In this sense, modern data products are true co-creations of hardware and software, where computational processes are as fundamental to discovery as the instruments that collect the light.

About the Author

Dr. Ajay Vibhute is currently working at the National Radio Astronomy Observatory in the USA. His research interests mainly involve astronomical imaging techniques, transient detection, machine learning, and computing using heterogeneous, accelerated computer architectures.

About airis4D

Artificial Intelligence Research and Intelligent Systems (airis4D) is an AI and Bio-sciences Research Centre. The Centre aims to create new knowledge in the field of Space Science, Astronomy, Robotics, Agri Science, Industry, and Biodiversity to bring Progress and Plenitude to the People and the Planet.

Vision

Humanity is in the 4th Industrial Revolution era, which operates on a cyber-physical production system. Cutting-edge research and development in science and technology to create new knowledge and skills become the key to the new world economy. Most of the resources for this goal can be harnessed by integrating biological systems with intelligent computing systems offered by AI. The future survival of humans, animals, and the ecosystem depends on how efficiently the realities and resources are responsibly used for abundance and wellness. Artificial intelligence Research and Intelligent Systems pursue this vision and look for the best actions that ensure an abundant environment and ecosystem for the planet and the people.

Mission Statement

The 4D in airis4D represents the mission to Dream, Design, Develop, and Deploy Knowledge with the fire of commitment and dedication towards humanity and the ecosystem.

Dream

To promote the unlimited human potential to dream the impossible.

Design

To nurture the human capacity to articulate a dream and logically realise it.

Develop

To assist the talents to materialise a design into a product, a service, a knowledge that benefits the community and the planet.

Deploy

To realise and educate humanity that a knowledge that is not deployed makes no difference by its absence.

Campus

Situated in a lush green village campus in Thelliyoor, Kerala, India, airis4D was established under the auspicious of SEED Foundation (Susthiratha, Environment, Education Development Foundation) a not-for-profit company for promoting Education, Research. Engineering, Biology, Development, etc.

The whole campus is powered by Solar power and has a rain harvesting facility to provide sufficient water supply for up to three months of drought. The computing facility in the campus is accessible from anywhere through a dedicated optical fibre internet connectivity 24×7.

There is a freshwater stream that originates from the nearby hills and flows through the middle of the campus. The campus is a noted habitat for the biodiversity of tropical Fauna and Flora. airis4D carry out periodic and systematic water quality and species diversity surveys in the region to ensure its richness. It is our pride that the site has consistently been environment-friendly and rich in biodiversity. airis4D is also growing fruit plants that can feed birds and provide water bodies to survive the drought.