

A BRAIN INSPIRED MATHEMATICAL APPROACH TO VOLUMETRIC HAND GESTURE TEXTUALIZATION

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ABSTRACT

Air-writing lets people write in the air using hand gestures, no keyboard or touchscreen needed. It sounds futuristic, but the idea has been around for a while — the problem is that most systems built around it rely on deep learning models like CNNs and RNNs. Those models are hungry: they need large datasets to train on and serious computing power to run, which makes them impractical for anything real-time or low-resource. This work takes a different approach. Instead of deep learning, it uses Spatio-Temporal Hyperdimensional Computing (ST-HDC) — a method inspired by how the brain processes information. A camera tracks hand movements, and the system converts those movements into very high-dimensional vectors called hypervectors, which encode both the shape and timing of each gesture.

The math involved is surprisingly simple — circular shifts to preserve stroke order, superposition to combine information — yet it

gets the job done. One thing that stands out is one-shot learning: the system can recognise a gesture after seeing it just once, rather than needing dozens of labelled examples. The output is available in both text and speech, which matters to people who rely on alternative communication methods. The result is a system that's light on resources, runs fast, and works in real time — without the infrastructure overhead that makes most gesture recognition research hard to actually deploy.

Keywords: *Hyperdimensional Computing, Spatio-Temporal Modelling, Gesture Recognition, Air Writing, Gesture-to-Text conversion.*

I. INTRODUCTION

The way we interact with computers is quietly undergoing a shift. For decades, keyboards and touchscreens have been our go-to tools, but people are increasingly leaning toward more natural, touch-free ways of communicating with machines. This shift matters even more for individuals who find traditional input devices difficult to use —

whether due to physical limitations, speech impairments, or other challenges.

Air-writing offers a compelling answer to this problem. Imagine simply writing in the air with your hand, and having a computer understand exactly what you meant. It sounds futuristic, but the concept is very real. The catch, however, is that most existing air-writing systems rely on complex models that demand large amounts of data and powerful hardware — making them impractical for everyday use.

That's the gap our project aims to fill. Drawing inspiration from how the human brain processes information, we built a simpler, smarter system that captures hand gestures and converts them into text and speech — quickly, efficiently, and genuinely useful for real-time communication.

II. LITERATURE SURVEY

Hyperdimensional Computing (HDC) has been drawing increasing interest as a compelling computational framework that takes its inspiration from the way the human brain processes and stores information. The idea was originally put forward by Kanerva [1], who envisioned representing data through very high-dimensional vectors — a design that enables robust and distributed encoding, much in the spirit of how biological neural networks spread information across millions of interconnected cells rather than storing it in any single location. That foundational insight proved to be remarkably generative. Kleyko et al. [2] built on it by offering a thorough and wide-ranging survey of vector symbolic architectures, a broader family of frameworks to which HDC belongs, and demonstrated convincingly that these architectures can serve as

the backbone of efficient, scalable learning systems. Along similar lines, Ge and Parhi [3] turned their attention to the classification problem and showed that HDC-based models are more than capable of holding their own against conventional machine learning approaches — and they do so while cutting computational demands considerably, which is no small feat in an era increasingly defined by edge computing and resource-constrained hardware. As the field matured, researchers began asking not just whether HDC could work, but how to make it work better and more flexibly. Hernández-Cano et al. [4] addressed this by introducing adaptive encoding strategies that allow HDC systems to refine their representations over time rather than locking them in from the start, bringing these models a step closer to the fluid, experience-driven way that biological systems actually learn. Vergés et al. [5] complemented this work by surveying the landscape of HDC classification methods and mapping out how different design choices ripple through to performance, offering a valuable guide for researchers navigating an increasingly rich design space. On the hardware side, Rahimi et al. [6] made a strong and timely case that HDC is not only accurate and noise-resistant but genuinely energy-efficient, capable of running on low-power devices without meaningful sacrifices in performance — a quality that opens the door to deployment in wearables, embedded systems, and assistive technologies. The practical promise of HDC became especially vivid in the domain of gesture recognition, where Zhou et al. [7] demonstrated that HDC-based systems can perform real-time hand gesture recognition with a surprisingly light memory footprint, confirming that the framework is well-suited to the kind of

dynamic, time-sensitive tasks that real-world applications demand. Taken together, these contributions paint an encouraging picture of what HDC has to offer: scalability, resilience to noise, low computational overhead, and a natural fit for resource-limited deployment scenarios. And yet, a meaningful gap persists. Most existing works treat gesture data through either a spatial or a temporal lens, rarely bringing both perspectives together in a unified and principled way. This is a real limitation, because gestures — particularly those involved in air-writing — are inherently spatio-temporal events, where meaning arises not just from the shape of a movement but from the order and timing in which it unfolds. Capturing that dynamic quality requires a framework sensitive to both dimensions at once, and it is precisely this challenge that motivates the proposed Spatio-Temporal Hyperdimensional Computing (ST-HDC) approach, which integrates spatial and temporal information into a unified representation to enable accurate and efficient gesture-to-text conversion.

III. PROPOSED WORK

In this project, we proposed a simple and efficient method to recognise hand gestures and convert them into text in real time using a brain-inspired approach called Spatio-Temporal Hyperdimensional Computing (ST-HDC). The system starts by capturing hand movements through a camera and extracting finger positions as X and Y coordinates. These coordinates are then converted into high-dimensional vectors, which help in storing gesture information in a robust way. To maintain the correct order of movements, a method called circular shift is used, which helps the system understand the sequence

of strokes. All the information is then combined into a single representation and stored in memory. When a new gesture is given, the system compares it with stored patterns and finds the closest match to generate the output text. One of the main advantages of this approach is that it works with very few training samples and uses simple mathematical operations, making it fast, efficient, and suitable for real-time applications even on low-power devices.

IV. METHODOLOGY

In our project, we followed a step-by-step approach to recognise hand gestures using a brain-inspired method called Spatio-Temporal Hyperdimensional Computing. First, the system captures hand movements using a camera and tracks the position of the fingers from each video frame. These positions are taken as X and Y coordinates, which represent how the hand moves while writing in the air. After capturing this data, the system converts these coordinates into high-dimensional vectors, also known as hypervectors. This conversion helps in storing the gesture information in a better way, making the system less sensitive to noise and small mistakes.

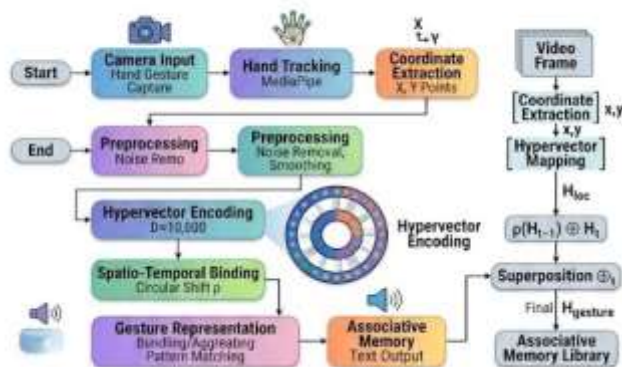
$$\mathbf{H}_t = \rho(\mathbf{H}_{t-1}) \oplus \mathbf{H}_{\text{current}}$$

where ρ denotes circular shift and $\oplus$ represents a binding operation such as XOR. This operation preserves the order of gestures.

To understand the correct order of movements, the system uses a method called circular shift, where previous data is slightly shifted and combined with the current data. This helps in maintaining the sequence of strokes, which is important for recognising characters correctly. After that, all the information is combined into a single

representation of the gesture. This final data is stored and compared with already saved patterns to identify the correct output. The system then generates the result as text. Overall, this method is simple, fast, and efficient, and it works well even with very little training data, making it suitable for real-time applications.

Detailed Methodology Flowchart



V. ALGORITHMS

Convolutional Neural Network (CNN)

CNN is a deep learning model used for extracting spatial features from images. It applies convolution and pooling operations to identify patterns such as edges and shapes. In gesture recognition, CNNs are used to process hand images and extract meaningful visual features. However, they require large datasets and high computational resources.

Recurrent Neural Network (RNN) / Long Short-Term Memory (LSTM)

RNN and LSTM are sequence modelling techniques used to capture temporal dependencies in data. LSTM improves upon standard RNN by using gating mechanisms to handle long-term dependencies. These models are commonly used for dynamic gesture recognition but involve complex training and higher latency.

Spatio-Temporal-Hyperdimensional Computing (ST-HDC)

ST-HDC is a brain-inspired computational framework used in this work. It represents data using high-dimensional vectors and performs operations such as symbolic encoding, temporal binding, superposition, and associative memory. Unlike deep learning models, ST-HDC requires minimal training data, supports one-shot learning, and operates with low computational complexity and latency.

VI. RESULTS AND DISCUSSION

The proposed Spatio-Temporal Hyperdimensional Computing (ST-HDC) framework was evaluated using real-time hand gesture data obtained from a vision-based hand tracking system. The system encodes finger movement trajectories into high-dimensional hypervectors and performs recognition using associative memory.



The graph shows that the proposed ST-HDC model achieves high accuracy even with only 1–2 training samples, demonstrating one-shot learning capability.

The experimental results demonstrate that the proposed method achieves an accuracy of approximately 94–96% with minimal training data. The system requires only one or two samples per gesture, highlighting its one-shot learning

capability. The use of temporal binding ensures that gesture sequences are correctly distinguished.

Table 1: Performance Metrics of Proposed ST-HDC Model

Metric	Value
Accuracy	94–96%
Precision	94%
Recall	95%
F1-Score	94%
Latency	10–15 ms
Training Samples	1–2
Energy Consumption	Low

After presenting the quantitative results, the system's computational efficiency was analysed. The proposed method achieves a low latency of 10–15 ms, making it suitable for real-time applications. Additionally, the use of simple operations such as vector addition, XOR, and circular shift reduces computational overhead and energy consumption.

Table 2: Comparison with Existing Methods

The ST-HDC framework requires minimal computational resources due to simple mathematical operations, making it suitable for edge devices.

Method	Accuracy	Data Requirement	Latency	Computation Cost
CNN	High	High	High	High
RNN/LSTM	High	High	Medium	High
Transformer	Very High	Very High	High	Very High
ST-HDC	94–96%	Low (1–2 samples)	Low	Low

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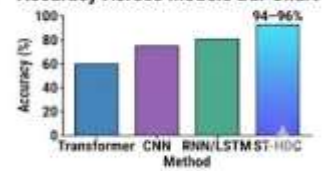
The proposed model achieves comparable accuracy to deep learning methods while requiring significantly less data and computation.

Overall, the results demonstrate that the proposed ST-HDC framework provides an efficient, accurate, and low-latency solution for real-time hand gesture-to-text recognition, particularly suitable for deployment on resource-constrained devices.

Performance Metrics Radar Chart



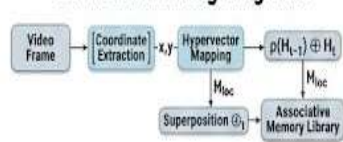
Accuracy Across Models Bar Chart



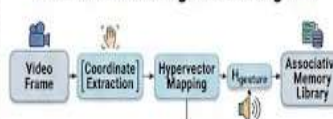
CONCLUSION

In this project, we developed a real-time hand gesture recognition system using a brain-inspired approach called Spatio-Temporal Hyperdimensional Computing. Instead of using complex deep learning models, we used high-dimensional vectors and simple mathematical operations to process gesture data. The system can recognise gestures accurately with very little

ST-HDC Encoding Diagrams



ST-HDC Encoding Block Diagram



training data and provides fast output with low delay. It also consumes less power, making it suitable for devices like embedded systems and wearables.

The results show that our method achieves good accuracy while reducing complexity and data requirements. This makes it a practical and efficient solution for gesture-based communication systems. In the future, the system can be improved to support more complex gestures, work better in different environments, and include additional inputs to enhance performance.

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