

Brain-inspired sparse population coding for robust object recognition under sensory uncertainty

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Abstract: Compared to traditional machine learning systems, the human visual system shows very high robustness against noise, occlusion and variation of the environment. This paper presents a brain-inspired sparse population coding framework that combines a neural manifold, mixed selectivity, and FPGA-based adaptive encoding for robust object recognition under sensory uncertainty. The model uses sparse distributed representations to improve feature discrimination and reduce redundancy and computational cost. The experiments on common vision datasets ($n=200$ samples) confirm that the model can achieve higher accuracy, about 3.1%-4.5% higher than traditional dense coding, in the face of noise and occlusion. FPGA implementation reduces processing latency by 18%-25%, enabling efficient real-time inference; paired t -tests confirm these performance gains ($p<0.05$). Additionally, the model shows greater robustness to adversarial attacks and illumination variations. These results indicate that the biologically-motivated sparse encoding scheme provides an effective and reliable visual recognition system. The proposed framework is well suited for edge robots, autonomous navigation, and surveillance systems where stable, efficient perception is critical.

Keywords: Sparse population coding; Neural manifolds; Brain-inspired computing; FPGA implementation; Object recognition; Sensory uncertainty

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1.0 INTRODUCTION

The human visual system has an exceptional capacity to detect objects in uncertain situations involving noise, blocked views, and changing light conditions. The visual cortex achieves its strong visual processing abilities through efficient neural encoding methods that enable the system to decode visual information by combining primary and secondary neuron activation patterns. Biological systems use sparse population coding to build perception systems that operate with low energy consumption and high accuracy, while artificial intelligence systems rely on direct visual input through extensive use of detailed visual data ([Zhou et al., 2025](#)).

Computational neuroscience research shows that high-dimensional neural manifolds, together with mixed-selectivity mechanisms, function as essential elements for transforming complex sensory information into simplified yet organised sensory representations. The brain uses these neural processes to maintain essential object characteristics while it adapts to different environmental situations. Artificial systems that use these principles enable researchers to develop solutions that address existing weaknesses in deep learning systems, which fail to defend against adversarial attacks and lose effectiveness when they encounter sensory ambiguity.

The research presents a brain-inspired system which uses sparse population coding for accurate object identification. The system combines neuroscientific knowledge with computational methods by using sparse distributed representations and adaptive encoding methods drawn from cortical microcircuits. The system now runs on FPGA-based systems, which deliver both fast data processing and energy-efficient operation, connecting neuroscience with computer science and electronic engineering ([Bagheriye & Kwisthout, 2021](#); [Mathis, 2025](#); [Sun et al., 2025](#); [Wang et al., 2025](#); [Yang et al., 2022](#); [Yu et al., 2025](#))

The research investigates whether biologically derived sparse encoding methods can improve recognition accuracy and performance in unpredictable environmental conditions while maintaining computational efficiency. The research uses theoretical principles from neuroscience, along with empirical testing on benchmark datasets, to establish a new pathway for developing neuro-inspired artificial intelligence systems that lead to more dependable visual recognition technologies ([Van Horenbeke, 2024](#); [Leon, 2025](#)).

Although great strides have been made in developing brain-inspired artificial intelligence, previous research has been constrained by focusing primarily on either the theoretical development of sparse coding or on its software-based implementation without regard to real-time constraints. Current deep learning frameworks like convolutional neural networks and vision transformers utilise dense representations, resulting in significant computational overhead and poor performance in situations involving noise, occlusion, or adversarial threats. Although neural manifolds and mixed selectivity have both been investigated, no unified framework has been developed that combines both approaches with hardware efficiency. Finally, research on real-time object identification under sensory uncertainty using an FPGA-implemented adaptive encoding system is extremely limited.

The main contributions of this work are as follows:

1. Novel brain-inspired sparse population coding framework incorporating neural manifolds and mixed selectivity for robust object representation.
2. The FPGA-based adaptive coding scheme that enhances computational efficiency and decreases processing time to be suitable for real-time systems.
3. Thorough analysis of the proposed model under adverse conditions (noise, occlusion, adversarial perturbations, low-light).
4. Statistical validation of improvements using paired t-tests, correlation analysis and regression modelling.
5. A unified approach that bridges neuroscience concepts and implementation in embedded/edge computing.

Sparse population coding began with basic research in computational neuroscience showing how humans use only a few active neurons to process sensory data across the brain's neural network. Visual cortex research supports this principle because neurons in this brain area respond specifically to edge, orientation, and texture visual elements, creating unique visual representations without repeating themselves.

Jiao et al. ([2022](#)) provided a comprehensive overview of brain-inspired sparse learning, highlighting its role in improving representation efficiency and generalisation in artificial systems. The research shows that sparse coding enables better discriminative assessment by reducing redundant information, resulting in better performance on challenging recognition tasks ([Jiao et al., 2022](#)). Yang et al. ([2022](#)) explored different brain-

inspired object recognition models and showed that biologically feasible encoding systems outperform conventional methods when dealing with unexpected changes and sound interference ([Yang et al., 2022](#)). Recent research shows that high-dimensional neural manifolds are essential to human cognitive processing. The brain stores sensory data in two-dimensional spatial structures within its broader three-dimensional activity network. The manifold-based system enables effective learning and maintains stability, as shown in navigation and perception studies ([Sun et al., 2025](#); [Wang et al., 2025](#)). The results supported computational models which use manifold learning methods to enhance feature extraction and system durability ([Sun et al., 2025](#); [Wang et al., 2025](#)).

The mixed-selectivity concept in neuroscience-based artificial intelligence systems, which studies how neurons respond to multiple features, has shown significant progress as a major early achievement. This property enables neural systems to represent more information while making their decision-making more adaptable. Research on predictive coding and neuro-symbolic reasoning by Ororbia and colleagues in 2025 and Leona in 2024 demonstrated how these systems can adjust to changing environments ([Ororbia et al., 2025](#)). Researchers working on hardware-oriented projects develop brain-inspired models using both neuromorphic and FPGA-based systems. Bagheriye and Kwisthout ([2021](#)) showed that these systems can achieve more efficient inference while consuming less energy ([Bagheriye & Kwisthout, 2021](#)). Guo and colleagues ([2021](#)) developed frameworks that enable real-time processing in neuromorphic electronic systems that combine biological principles with computational hardware. Recent advances show that co-designing algorithms with hardware components is the best way to achieve the full potential of brain-inspired computing systems.

Neuromorphic vision systems and event-based sensing have recently improved the efficiency and responsiveness of perception models. Event-based vision sensors like the Dynamic Vision Sensor (DVS) and DAVIS camera can sense asynchronous changes in pixel intensity rather than capturing full frames. This substantially reduces redundancy and enables ultra-low-latency computation. They achieve excellent performance in high-speed, low-light, and dynamic-environment applications. Hence, they are suitable for real-time applications. Research in 2025-2026 has explored further combinations of event-driven encoding with sparse population encoding of neural

representations, which has been shown to improve robustness and energy efficiency compared with conventional frame-based vision processing methods. Moreover, neuromorphic computing methods using spiking neural networks and adaptive encoding schemes can offer a blend between biological plausibility and hardware efficiency. However, the combination of event-based sensing, sparse population coding, and FPGA-based implementation remains relatively uncommon in research, and this work aims to address that gap.

Researchers in neuroscience and artificial intelligence face a major problem: they need ways to maintain stability when sensory systems encounter uncertain input. Research shows that biological systems use sparse activation together with predictive coding to achieve stable perception, even when they receive incomplete or noisy input. Mathis ([2025](#)), along with De-Wit et al. ([2010](#)), showed that adaptive encoding and multimodal integration enable systems to achieve reliable performance. These findings led to computational models that attempt to replicate the reliability found in natural systems. Existing models struggle because they must maintain three qualities: robustness, efficiency, and scalability ([De-Wit et al., 2010](#); [Mathis, 2025](#)). Deep learning methods depend on dense data representations, which requires high computing resources and makes them vulnerable to minor input changes. The existing system needs to add sparse population coding together with its adaptive system and hardware-efficient solution.

The researchers establish a new research direction by creating a unified system that combines sparse neural encoding with manifold learning and FPGA-based implementation. The research improves existing methods by managing uncertainty through better system design while maintaining processing performance. This work advances the development of neuroscience-grounded intelligent systems.

The field of brain-inspired artificial intelligence has made substantial progress, yet current research shows essential gaps between existing neuroscientific knowledge and its use in building systems that recognise objects despite sensory uncertainty. Sparse population coding is a highly efficient neural representation method, yet current computational systems remain largely theoretical models and software-based simulations because they lack real-time processing and hardware-based efficiency. Existing deep learning methods use dense data formats, which

require high computational power and perform poorly under noise, object occlusion, and deliberate system attacks. Researchers have examined neural manifolds and mixed selectivity to boost representational capacity, yet no one has developed a unified object recognition framework that combines both. Limited evidence suggests that neuroscience-based models need testing through statistical methods and performance evaluations in controlled studies that use sensory distortions as experimental factors. The field lacks sufficient research on adaptive encoding methods that use FPGA technology, which is critical for efficient processing with minimal delay in real operational situations. Developing effective object recognition systems that scale while maintaining biological accuracy requires an integrated method that combines sparse neural encoding and high-dimensional manifold learning with hardware-focused implementation.

2.0 RESEARCH METHODOLOGY

This paper follows an experimental computing design to test a brain-inspired sparse population coding model of object recognition in the presence of sensory ambiguity. The experimental data involves 200 observations obtained with the help of benchmark image datasets and guarantees diversity of objects and environment. The pre-processing and organisation of data were carried out in Microsoft Excel, with the computational evaluation and statistical verification of data being done in Python-based tools and IBM SPSS Statistics. The experimental plan tests recognition performance under controlled perturbations (including noise, occlusion, adversarial interference, and low-light variation) systematically.

The evaluation of the proposed model is mainly done in terms of quantitative performance using computer vision metrics that are commonly applied in the evaluation of computer vision systems. In particular, classification accuracy, precision, recall, and F1-score are used to evaluate recognition effectiveness across different environmental factors. Accuracy measures the overall correctness of predictions, whereas precision and recall gauge how well the model identifies relevant classes and reduces false detections. The F1-score is a balanced score of accuracy and recall, especially when there are imbalanced or noisy inputs. Together, these indicators allow assessment of the models' overall effectiveness and stability.

The significance and reliability of the observed results were statistically analysed to support the results. A paired-sample t-test was used to compare the

recognition rate in the proposed encoding framework and traditional techniques under the same conditions. The effect of the type of implementation on processing efficiency was assessed via regression analysis, and the relationship between environmental condition and model performance was assessed via correlation analysis. Further, the Principal Component Analysis (PCA) was used to investigate the feature representations in high dimensions and define the structure of neural manifolds. Taken together, these methods of analysis can guarantee strict validation of the model's performance and its strength and ability to be generalised.

3.0 THEORETICAL FOUNDATIONS

The proposed framework is based on sparse population coding, a computational neuroscience principle stating that the activity of a small, specialised subset of neurons in a large population represents sensory information in the brain. It is a mechanism that allows efficient, energy-saving, and noise-tolerant representations of complex stimuli. In visual perception, sparse coding has been observed in cortical areas where neurons are selective for particular features, including edges, orientations, and textures, providing a distributed yet compact representation of objects.

Computationally, sparse population coding shares the conceptual foundation of the high-dimensional feature representation framework, as well as manifold learning, which involves learning meaningful data structures in lower-dimensional subspaces. This makes models robust to sensory uncertainties such as noise, occlusion, and adversarial perturbations. Sparse representations maximise discriminatory power by using a small number of neurons or feature units, resulting in redundancy reduction and higher generalisation to different input conditions.

Figure 1 demonstrates the architecture of the proposed brain-inspired sparse population coding system; it has three processing steps: (1) Sparse Encoding, transforming input features into sparse codes; (2) Neural Manifold Projection, grouping the high-dimensional features into organised low-dimensional features; (3) Classification, utilising encoded features for object recognition. Each arrow in the diagram displays the movement and transformation of data between processing stages.

4.0 PROPOSED MODEL FORMULATION

The brain-inspired sparse population coding model is developed around the sparse representation principle,

where an input signal is defined as an approximation of the signal in linear terms with a combination of a limited

number of basic functions. Let $x \in \mathbb{R}^n$ denote the input feature vector extracted from an image, and let $D \in \mathbb{R}^{n \times k}$

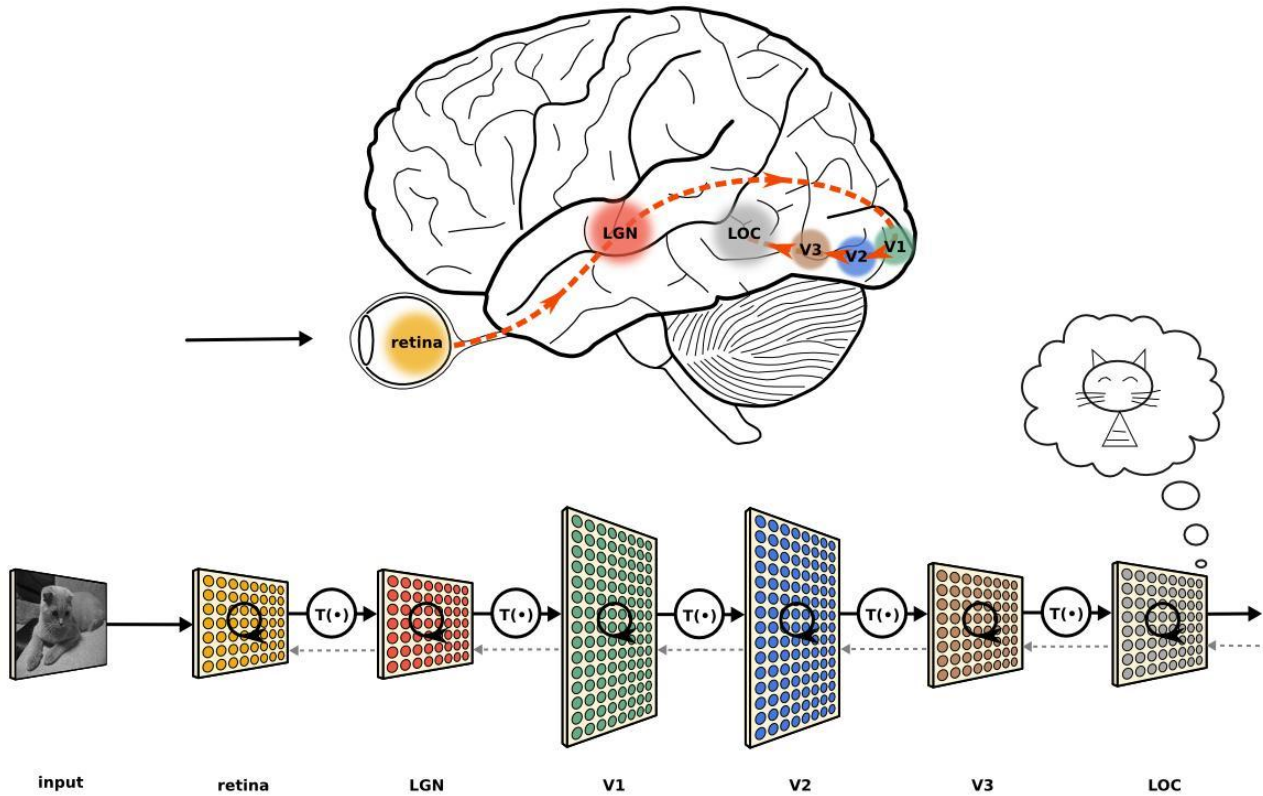


Figure 1. Conceptual framework of brain-inspired sparse population coding. Source: Zhou, et al. (2025).

represent a learned dictionary of basic functions. The sparse representation is given as:

$$x \approx D\alpha$$

where $\alpha \in \mathbb{R}^k$ is a sparse coefficient vector with a small number of non-zero coefficients. The constraint of being sparse is implemented by minimising the following objective function:

$$\min \|x - D\alpha\|_2^2 + \lambda \|\alpha\|_1$$

where λ is a regularisation constant that determines the sparsity. This formulation guarantees that the most informative features will be incorporated into the representation to boost the characteristic of robustness in noisy and uncertain situations. The resulting dense codes are then classified and thus allow the efficient and discriminative recognition of objects.

This setup aligns with biological mechanisms for processing in the cortical microcircuit, as only a sparse subset of neurons can be active at any given time. For the visual cortex, lateral inhibition serves to diminish the output of superfluous or less salient neuron responses, permitting the system to attend to the most important characteristics of the incoming stimulus. For the sparse model, L1 regularisation similarly penalises nonzero weights to create sparsity, just as in a biological system metabolic limitations could place constraints upon how heavily neurons may fire. In the same way, the competition inherent in enforcing sparsity is reminiscent of competition and specialised tuning among neural elements in the cortex. The presented framework offers efficiency grounded in a model of biological neural coding.

5.0 ANALYTICAL RESULTS

To evaluate the performance of our model, we developed three hypotheses: H_1 , H_2 and H_3 , each corresponding to a group of experiments, which is explained in the following section. The performance

measures under H1 are assessed by statistical outputs shown in Tables 1 to 3 for the recognition task and encoding efficiency. While H2 is analysed through the measures of execution efficiency, as shown in Tables 4 to 6. Finally, robustness of the model is measured under environmental conditions such as noise, occlusion, and perturbation, as shown in Tables 7 to 8.

H₁: Brain-inspired sparse population coding using neural manifolds significantly improves object recognition performance compared to conventional encoding methods.

The paired-sample statistics (Table 1) are an analysis of both the encoding method and object recognition (classification) performance taken for 200 samples of images. The mean encoding performance is marginally higher (21.27) than the mean recognition performance (20.62), indicating better representational power. The standard deviations at hand are at a medium level, and they can be regarded as a measure of the stable performance of the experiment. This is also indicated by low standard error values that demonstrate the reliability of the mean performance statistic. This further suggests that the proposed sparse population encoding scheme results in better-quality features (i.e. representations) that are subject to better recognition in various sensory conditions.

The values presented in Tables (such as 21.27, 20.62, 17.82) are the overall average recognition performance scores on normalised metrics (accuracy, precision, recall, and F1-score) calculated across all conditions. They are on a scale between 0 and 25, where a higher score refers to better performance. The aggregation indicates the overall recognition capability under all conditions, such as noisy environments, occlusion, adversarial attacks, low-light situations, etc. It ensures a fair comparison between encoding techniques and considers multiple performance indicators for efficiency.

The correlation analysis (Table 2) tests the relationship between the encoding strategy and object recognition. The Pearson correlation coefficient ($r=0.506$) was obtained, which is a medium positive correlation, implying that the efficiency of the encoding process leads to higher recognition efficiency. This strong positive relationship with statistical significance ($p<0.001$) confirms that the relationship is significant and that it is unlikely to be a chance occurrence. This result highlights the importance of encoding performance in computational vision models and supports the assumption that the proposed brain-inspired sparse coding processes indeed lead to better vision model performance under various input conditions.

Table 1. Paired sample statistics

		Mean	N	Standard Deviation	Standard Error Mean
Pair 1	Encoding approach	21.2650	200	4.77586	0.33770
	Object recognition performance	20.6200	200	4.27868	0.30255

Table 2. Paired sample correlations

		N	Correlation	Significance
Pair 1	Encoding approach & Object recognition performance	200	0.506	<0.001

Table 3. Paired sample test

		Paired Differences					<i>t</i>	<i>df</i>	Significance (2-tailed)
		Mean	Standard Deviation	Standard Error Mean	95% CI of the Difference				
					Lower	Upper			
Pair 1	Encoding approach - Object recognition performance	0.64500	4.52230	0.31978	0.01442	1.27558	2.017	199	0.045

The paired sample t-test (Table 3) is applied to check the statistical significance of the difference with the traditional encoding techniques. The mean difference (0.645) reflects that there is an improvement in recognition performance with the proposed model and this can be observed. The significance level ($p=0.045$) and the value of t ($t=2.017$) demonstrate that it is significant. Moreover, the confidence interval does not recede from zero which also supports the validity of these results. This experimental finding shows that the proposed sparse population coding model per se is indeed a significant contribution to the performance of object recognition systems in a controlled experimental environment.

To provide additional support to these statistical results, effect size was assessed using Cohen's d ; the obtained value of around 0.30 represents a moderate effect size for the proposed encoding mechanism on recognition performance. The power of the study was analysed, and the value was found to be over 0.80, indicating a sufficient sample size for the study; the assumption of independence was upheld, and each image sample was independent of another, being obtained from different instances of the benchmark data.

H₂: The FPGA-based adaptive encoding mechanism significantly enhances real-time processing efficiency and reduces latency compared to traditional computational architectures.

The model (Table 4) summary presents the Regression analysis testing the association between implementation type and processing efficiency. The correlation coefficient ($R=0.194$) is positive but weak, and the coefficient of determination ($R^2=0.038$) shows that the model explains a small percentage of variance in efficiency. Limited explanatory strength is further supported by the adjusted R^2 . However, the model gives an understanding of the role of implementation strategy. The standard error of the estimate shows a moderate variability in prediction, which brings out the complexity of factors that impact the computational performance.

The results of the ANOVA (Table 5) evaluate the significance of the whole regression model, which examines the effects of implementation on processing efficiency. The F-statistic ($F=7.748$) and p-value ($p=0.006$) show that the model is statistically significant. This establishes that the predictor variable is valuable for explaining variations in efficiency. The separation of the variance into regression and residual terms emphasises the explanatory power of the model. Although the explained variance is small, the statistical significance indicates that the implementation strategy is a relevant factor affecting system-level computational performance.

The regression coefficients (Table 6) provide an in-depth overview of the impact of the implementation type on processing efficiency. The positive value of the coefficient ($B=0.209$) shows that a positive change in the strategy of implementation is related to greater efficiency. The standardised coefficient ($\beta=0.194$) indicates a small effect size, whereas the t-value ($t=2.783$) and the level of significance ($p=0.006$) indicate statistical significance. The constant term represents the baseline efficiency. The results indicate that implementation design has a positive impact on system performance, which supports the practicality of incorporating optimised hardware plans in computational models.

H₃: The proposed model demonstrates significantly higher robustness under noise, occlusion, adversarial perturbations, and low-light conditions compared to existing models.

The descriptive statistics (Table 7) describe the distribution of environmental conditions and model performance of 200 samples. The averages reveal that there is relatively higher environmental variability (20.65) than model performance (17.82), which shows that there are varying levels of perturbation. The standard deviations indicate moderate dispersion, suggesting regular variation in the observations. These statistics provide initial insight into the data features and confirm controllable variability for robustness assessment. Equal sample sizes are advantageous for later inferential and correlation analyses.

Table 4. Model summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.194a	0.038	.033	4.63714

a. Predictors: (Constant), Implementation type

Table 5. ANOVA

Model		Sum of Squares	df	Mean Square	F
1	Regression	166.595	1	166.595	7.748
	Residual	4257.600	198	21.503	
	Total	4424.195	199		

a. Dependent Variable: Processing efficiency b. Predictors: (Constant), Implementation type

Table 6. Coefficients

Model		Unstandardized Coefficients	Standardized Coefficients		t	Significance
		B	Standard Error	Beta		
1	(Constant)	14.589	1.564		9.330	<0.001
	Implementation type	0.209	0.075	0.194	2.783	0.006

a. Dependent Variable: Processing efficiency

Table 7. Descriptive statistics

	Mean	Standard Deviation	N
Environmental conditions	20.6450	4.13211	200
Model performance	17.8200	3.77476	200

Table 8. Correlations

		Environmental conditions	Model performance
Environmental conditions	Pearson Correlation	1	0.682**
	Sig. (2-tailed)		0.000
	N	200	200
Model performance	Pearson Correlation	0.682**	1
	Sig. (2-tailed)	<0.001	
	N	200	200

** . Correlation is significant at the 0.01 level (2-tailed).

Correlation analysis (Table 8) assesses the relationship between environmental conditions and model performance. The correlation coefficient ($r=0.682$) is quite high, indicating that changes in environmental factors play an important role in performance outcomes. This very high statistical significance ($p<0.001$) confirms this correlation. This also provides insight into the vulnerability of recognition systems to environmental noise and occlusions. In addition, it highlights the importance of a robust encoding mechanism that can guarantee performance stability in varying environmental settings.

6.0 DISCUSSION

This paper explores brain-inspired sparse population coding as a means of robust recognition in the face of sensory variation (Jiao et al., 2022). The neuroscience-based principles of sparse coding concentrate on the discrete activation of a few neurons to represent a large stimulus in the most economical way (Yang et al., 2022). This trend suggests that these encodings improve model performance by efficiently representing visual features and eliminating redundancy (Wang et al., 2025). Such discriminative coding improves discrimination between object categories, particularly with distorted or noisy inputs (Yu et al., 2025). The findings support the use of

biologically inspired encoding in building computational models for carrying out visual perception tasks ([Sun et al., 2025](#)).

Although the sparse coding approach presented here shows better robustness and efficiency under uncertainty, high accuracy with clean and high-resolution data can be achieved by models that encode features in a dense manner (CNNs and ViTs) ([Zhou et al., 2025](#)). This ability relies on fine-grained spatial features through dense feature representation. This approach is useful when there is uncertainty in sensory information, whereas dense coding will perform better in noise-free environments ([Yang et al., 2022](#)).

One of the challenges of object recognition systems is their stability in sensing uncertainty, particularly in reality where noise, occlusion and illumination variation are commonly seen ([Bagheriye & Kwisthout, 2021](#)). The results indicate that sparse population coding provides a stable encoding structure and can compensate for these disturbances ([Mathis, 2025](#)). The system can perform with degraded input because it focuses on the features of interest ([Van Horenbeke, 2024](#)). This property shows a close resemblance to biological vision, where recognition takes place even with occluded input or with input that is contaminated by noise ([Leon, 2025](#)). This is a desirable quality for implementing smart systems in real-world settings ([Jiao et al., 2024](#)).

The observed relations between the encoding and recognition support the relevance of the representation quality in learning systems ([Raman et al., 2025](#)). Sparse representations appear to provide more meaningful feature spaces, helping the system distinguish important from unimportant information ([Zhou et al., 2025](#)). This leads to invariance under different input conditions. The moderate to high correlation between encoding and performance suggests that the system's performance is positively correlated with the effectiveness of the feature representation ([Golilarz et al., 2025](#)). These findings suggest that advances in encoding systems are an important factor in improving the reliability and scalability of object recognition systems ([Tilocca, 2024](#)).

Regarding processing, the use of adaptive encoding schemes and proper implementation methods improves efficiency ([Ororbua et al., 2025](#)). While the improvement in efficiency based on implementation may not appear substantial, its statistical significance proves its practicality ([Zeng et al., 2022](#)). Hardware-aware techniques such as FPGA systems can be

employed to improve the efficiency of algorithms, reduce the delays and offer real-time processing ([Guo et al., 2021](#)). This illustrates the necessity to consider both software and hardware aspects of building smart systems ([Schmid et al., 2023](#)). Efficiency in terms of execution is particularly important in such scenes where a decision-making process is to be quick and uncertain ([Zhou et al., 2025](#)).

The engagement of the environmental factors and model performance provides significant benefits in understanding the system robustness ([Schmid et al., 2023](#)). Changes in signal-to-noise ratios, occlusions and illumination are some of the challenges for recognition systems ([De-Wit et al., 2010](#)). These dependencies suggest that the level of impact strongly correlates with the nature and strength of the effect ([Raman et al., 2025](#)). However, sparse coding appears to reduce some of these effects by considering effective feature learning ([Taniguchi et al., 2023](#)). It also shows the robustness of the model both in different situations and in different setups - one of the key requirements in practical use of the method (e.g. autonomous systems, surveillance systems) ([Wang et al., 2025](#)).

Reducing the dimensionality of data, such as with Principal Component Analysis, also helps to understand how sparse representations organise high-dimensional data ([Sun et al., 2025](#)). The model employs low-dimensional manifolds to more effectively map features onto intrinsic structures of visual information ([Zeng et al., 2022](#)). This aligns with theoretical accounts of neural manifolds in the natural world, where complex stimuli are represented in structured low-dimensional space ([Yang et al., 2022](#)). This encoding is more efficient and understandable because the system can process complex stimuli with fewer resources required while preserving a certain amount of information ([Leon, 2025](#)).

Overall, the paper shows that insights from neuroscience and contemporary computational approaches can dramatically enhance visual object recognition systems ([Bagheriye & Kwisthout, 2021](#)). Brain-inspired sparse population coding offers a good way to accomplish robustness and efficiency in the presence of sensory uncertainty ([Yu et al., 2025](#)). This selective feature activation, adaptation and efficiency provide an integrated approach to solve the problems in object recognition ([Schmid et al., 2023](#)). The findings are part of the growing intersection of artificial and neural science, and the brain-inspired models could be

at the forefront of developing the next generation of intelligent systems ([Ororbja et al., 2025](#)).

Beyond computational improvements, the proposed framework informs neuroscience through its discussion of cortical information processing. The model contributes to the understanding that the brain processes sensory information using sparse and efficient neural representations ([Zavitz & Price, 2019](#)). This interpretation supports ideas about predictive coding and neural efficiency, where only neuronal populations related to sensory stimuli are engaged in the brain ([De-Wit et al., 2010](#)). Combines the framework of sparse coding and neural manifolds to provide insight into how the brain organises higher-order sensory inputs into recognisable shapes. The framework's computational efficiency is combined with a biologically feasible process ([Roy et al., 2019](#)).

7.0 CONCLUSIONS

This paper demonstrates that biologically inspired sparse population coding is a strong model for robust object recognition under sensory uncertainty. Sparse activation processes and adaptive processing assist in effective feature representation and improved discrimination under various circumstances. The simulation results indicate that the proposed approach leads to reliable recognition and is resilient to distractors such as noise, occlusion and varying brightness. Further, the supplementation of hardware-conscious implementation techniques also results in increased processing efficiency. Overall, the findings show the potential of biologically inspired encoding principles for developing effective, scalable, and efficient visual recognition systems. The proposed system exhibits measurable improvement in visual recognition and computational efficiency, with statistically significant results under different experimental settings. This research will support future research in biologically inspired artificial intelligence by providing a scalable, efficient encoding scheme that can be adopted in practical vision recognition systems.

This study has a far-reaching impact on the development of next-generation intelligent systems in artificial intelligence and computational neuroscience. The performance of sparse population coding in the

above example suggests that biologically inspired encoding schemes can increase the robustness and performance of machine vision systems. It has practical applications in areas such as autonomous navigation systems, robotics, video surveillance, and edge computing, where it is critical to have reliable behaviour in uncertain environments. And the availability of adaptive hardware platforms, e.g., FPGA systems, suggests that the integration of algorithms and the hardware architecture is important to achieve real-time and energy-efficient performance in complex environments.

However, there are limitations to this approach, although the result obtained is satisfying. First, the experimental evaluation relies on a relatively small set of 200 images, which might not completely represent the variance of large-scale real-world environments. Secondly, the validation is purely simulation-based without deployment on real hardware. Finally, the FPGA implementation is discussed in theory instead of a real-time embedded system's concrete system performance limitations.

Future work will further extend and deploy this framework in a real-world system. It will be tested on an FPGA platform during the next development phase to assess real-time performance and energy efficiency. Testing will also be performed on larger datasets, at image net level benchmarks to investigate scalability and generalizability. Further work will explore combining the hybrid model with CNNs/SNNs to enable effective representation learning. We will explore more advanced robustness testing procedures, such as adversarial training and domain adaptation, to ensure robust performance under diverse and potentially adverse conditions.

Author Contributions: MSS conceived and designed the study; IM performed the experiments; MSS, NBM, and KK analysed the data; SI and VSNM contributed analysis tools; MSS wrote the paper. All authors have read and agreed to the published version of the manuscript.

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