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Pattern recognition in computer vision using discrete structures and deep learning

Rashmi Ashtagi [§]
Department of Computer Engineering and Technology
Dr. Vishwanath Karad MIT World Peace University
Kothrud
Pune 411038
Maharashtra
India

Anant Kaulage [†]
Department of Computer Science and Engineering
MIT Art, Design and Technology University
Pune 412201
Maharashtra
India

Anusha Pai *
Department of Computer Engineering and Technology
Dr. Vishwanath Karad MIT World Peace University
Kothrud
Pune 411038
Maharashtra
India

Ranjeet Vasant Bidwe [‡]
Department of Computer Science and Engineering
Symbiosis Institute of Technology
Pune Campus
Symbiosis International (Deemed University)
Pune 412115
Maharashtra
India

[§] *E-mail:* **rashmiashtagi@gmail.com**
[†] *E-mail:* **anant.kaulage1@gmail.com**
* *E-mail:* **anusha.pai@mitwpu.edu.in (Corresponding Author)**
[‡] *E-mail:* **ranjeetbidwe@hotmail.com**

Vaishali Rajput [@]
Department of Artificial Intelligence and Data Science
Vishwakarma Institute of Technology
Pune 411037
Maharashtra
India

Basavaraj Madagouda [#]
Department of Computer Science and Business Systems
S. G. Balekundri Institute of Technology
Belagavi 590010
Karnataka
India

Abstract

This work looks into ways to use deep learning and discrete mathematical structures together to make computer vision pattern recognition better. The suggested mixed models combine vector metric spaces, orthogonal sets, and discrete representations to make them better at finding features, being stable, and being easy to grasp. The technology uses novel data preparation tools and cutting-edge deep neural architectures that are based on discrete math's to record intricate visual patterns. An in-depth architectural design and processing flow are shown, along with custom loss functions and optimization techniques that are used in training methods. It was tested and found that this way works better and needs fewer computers power than others.

Subject Classification: *35B36.*

Keywords: *Pattern recognition, Discrete structures, Deep learning, Computer vision, Vector metric spaces.*

1. Introduction

Pattern recognition is a key computer vision job. It allows computers interpret visual data for object detection, picture classification, and scene comprehension. Traditional approaches employ continuous mathematical models and handcrafted features, making it difficult to capture discrete and organized visual patterns in complex situations [1, 2]. Discrete mathematics systems, which include vector metric spaces, orthogonal sets, and sequences, are very useful for representing and analyzing records that has herbal combinatorial and structural features. Combining those separate systems with deep learning, which is superb at creating hierarchical models from massive datasets [3], should enhance the performance and ease of perception of pattern popularity.

[@] *E-mail:* **vaishali.rajput@vit.edu**
[#] *E-mail:* **basavarajmadagouda@gmail.com**

Current upgrades in deep neural networks have changed laptop vision with the aid of making it feasible to do a huge variety of jobs with magnificent accuracy [4, 5]. Figure 1 suggests the hybrid discrete structures and deep learning framework.

But there are still issues with how solid, generic, and simple to describe taught qualities are Adding discrete mathematical concepts to neural architectures may help models by giving them the theoretical rigour and structural insights that discrete frameworks provide [6]. This observes suggests a new combo approach that combines discrete structures with deep getting to know methods to make sample reputation better. We use discrete illustration-based totally data guidance strategies, network architectures with orthogonally constraints, and training techniques that work high-quality for those combined fashions [7,8]. We display that our technique is extra correct and uses much less computing power than other methods by using strolling sizeable checks on trendy datasets. This take a look at fills inside the blanks among discrete mathematics and deep learning; growing a sturdy and expandable framework for future computer vision makes use of [9].

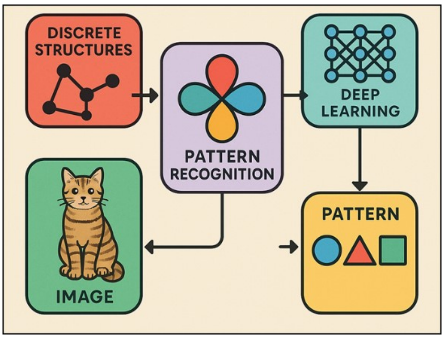

Figure 1
Integrated Framework of Pattern Recognition in Computer Vision Using Discrete Structures and Deep Learning

2. Proposed Methodology

2.1. *Hybrid models with discrete structures and deep learning*

Deep neural network designs and the hybrid model are each made up of different mathematics ideas, such as vector degree areas and orthogonal units [10], with this combination; both hierarchical feature learning and the recording of structure trends are possible. Discrete parts help with extracting and representing features, and deep learning layers describe complicated connections that don't follow a straight line. They make pattern recognition for computer vision jobs more reliable and easier to understand when used together [11].

Definition (Vector Metric Space): A vector metric space (V, d) is a vector space V equipped with a metric $d : V \times V \rightarrow \mathbb{R}$ satisfying:

$$d(x,y) \geq 0, d(x,y) = 0 \; iff \; x = y$$
$$d(x,y) = d(y,x)$$
$$d(x,z) \leq d(x,y) + d(y,z)$$
$$d(x + a, y + a) = d(x,y)$$

(Discrete-Orthogonality Constraint):

$$\langle u, v \rangle = 0$$

Theorem (Orthogonal Decomposition): *Any vector x ∈ V can be decomposed uniquely as*

$$x = x_{\parallel} + x_{\perp}, where \left\langle x_{\parallel}, x_{\perp} \right\rangle = 0 \quad (1)$$

Proof: By projection onto subspace defined by x_||, residual is orthogonal satisfying inner product zero.

(Hybrid Model Feature Mapping):

$$y = f_{\theta(T_{d(x)})} \quad (2)$$

(Discrete Transform Example - Fourier):

$$T_{d(x)(k)} = \Sigma_{\{n=0\}}^{\{N-1\}} x(n) e^{\left\{-i\, 2\pi \frac{kn}{N}\right\}} \quad (3)$$

(Loss with Orthogonality Regularizer):

$$\mathcal{L} = \mathcal{L}_{task} + \lambda \, \Sigma_{\{i \neq j\}}^{2} \left| \left\langle w_i, w_j \right\rangle \right| \quad (4)$$

Equation 10 (Gradient Update Rule for Weights W):

$$W^{\{t+1\}} = W^{t} - \eta \, \nabla_{W} \mathcal{L} \quad (5)$$

Equation 11 (Model Output Mapping):

$$\hat{y} = \sigma\left(W \, f_{\theta(T_{d(x)})} + b\right) \quad (6)$$

2.2. *Data representation and preprocessing strategies using discrete frameworks*

Discrete frames are used in data cleaning to turn raw visual sources into organised forms. Some methods used are mapping image data into vector measure spaces and getting orthogonal feature groups. These discrete changes keep the natural qualities of the data and lower its dimensions, which makes learning more efficient. This preprocessing improves the ability to tell the difference between features, which leads to better model agreement and accuracy in later steps of deep learning.

Definition (Orthogonal Set): Set {v_1, v_2, ..., v_m} ⊆ V is orthogonal if $\left\langle v_i, v_j \right\rangle = 0, for \; i \neq j$

(Vector Representation of Image Patch):

$$p = [p_1, p_2, \dots, p_n]^{T} \quad (4)$$

(Discrete Wavelet Transform (DWT)):

$$c = W\,p \tag{5}$$

(Normalization of Feature Vector):

$$p_{norm} = \frac{(p - \mu)}{\sigma} \tag{6}$$

(Dimensionality Reduction via PCA):

$$z = U_k^T (p - \mu) \tag{7}$$

(Sparse Coding Representation):

$$p \approx D\,\alpha,\ \left|\left|\alpha\right|\right|_0 \leq s \tag{8}$$

(Orthogonal Matching Pursuit for Sparse Coding):

$$\alpha = argmin_\alpha \left|\left|p - D\,\alpha\right|\right|_2^2, s.t. \left|\left|\alpha\right|\right|_0 \leq s \tag{9}$$

(Feature Selection Criterion):

$$\max \_\{v\_i\}\ Var(v\_i), subject\ to\ orthogonality$$

2.3. *Architecture details and algorithmic flow*

In a logical flow, the design blends separate sections with deep neural layers. Discrete filtering starts by turning incoming data into ordered vectors. These are sent through stages that enforce orthogonally limits to help make features independent. After that, fully linked and convolutional layers learn how to create hierarchical models. Algorithmic flow combines discrete operations with backpropagation to train a model from start to finish, achieving a balance between deep learning freedom and structure regularization.

Definition (Feedforward Layer):

$$\text{Equation 20. } L(h) = \phi(W\,h + b) \tag{10}$$

(Orthogonality-Enforced Weight Matrix):

$$W^T W = I \tag{11}$$

(Algorithmic Step - Forward Pass):

$$h^{\{(l+1)\}} = \phi\left(W^{\{(l)\}h^{\{(l)\}}} + b^{\{(l)\}}\right) \tag{12}$$

(Backward Pass - Gradient Computation):

$$\delta^{\{(l)\}} = \left(W^{\{(l+1)\}}\right)^T \delta^{\{(l+1)\}} \circ \phi'\left(h^{\{(l)\}}\right) \tag{13}$$

(Weight Update with Orthogonality Projection):

$$W^{\{t+1\}} = Proj_{\mathcal{O}(W^t - \eta\,\nabla_W \mathcal{L})} \tag{14}$$

(Batch Normalization Transform):

$$\hat{h} = \frac{(h - \mu_B)}{sqrt(\sigma_B^2 + \varepsilon)} \tag{15}$$

Algorithmic Flow Summary):

$$Input \rightarrow Discrete\ Transform \rightarrow Orthogonal\ Layers \rightarrow Dense\ Layers \rightarrow Output$$

(Activation Functions Examples):

$$ReLU(x) = \max(0, x),\ \sigma(x) = \frac{1}{1 + e^{\{-x\}}} \tag{16}$$

2.4. *Training protocols, loss functions, and optimization techniques*

To ensure orthogonality and sparsity, training uses unique loss functions that mix standard classification mistakes with discrete structure penalties. For fast convergence, optimisation uses adaptable algorithms such as Adam. Regularisation methods keep precise limits while stopping overfitting. Dropout and batch normalisation make generalisation better. The procedure makes sure that the training dynamics are stable, which makes the mixed model more accurate and easier to understand when it comes to pattern recognition tasks.

Definition (Cross-Entropy Loss):

$$\mathcal{L}_{CE} = -\Sigma_i y_i \log(\hat{y}_i) \tag{17}$$

(Orthogonality Regularization Term):

$$\mathcal{L}_{orth} = \Sigma^2_{\{i \neq j\}|\langle w_i, w_j \rangle|} \tag{18}$$

(Total Loss Function):

$$\mathcal{L} = \mathcal{L}_{CE} + \lambda\, \mathcal{L}_{orth} \tag{19}$$

(Gradient Descent Update):

$$\theta^{\{t+1\}} = \theta^t - \eta\, \nabla_\theta \mathcal{L}(\theta) \tag{20}$$

(Adam Optimizer Moment Estimates):

$$m_t = \beta_1 m_{\{t-1\}} + (1 - \beta_1)\nabla_\theta \mathcal{L},$$
$$v_t = \beta_2 v_{\{t-1\}} + (1 - \beta_2)(\nabla_\theta \mathcal{L})^2$$

(Adam Parameter Update):

$$\theta^{\{t+1\}} = \theta^t - \eta \left(\frac{\hat{m}_t}{(\sqrt{\hat{v}_t} + \varepsilon)}\right) \tag{21}$$

(Dropout Regularization):

$$h^{\{drop\}} = h \circ r,\ r \sim Bernoulli(p) \tag{22}$$

(Early Stopping Criterion):

Stop training if $\mathscr{L}$_val does not improve for k epochs

3. Results

On test datasets, the mixed model did a better job of recognizing patterns and being more stable than basic deep learning methods. It was easier to show features with discrete structures, which also cut down on overfitting and the cost of computing.

Table 1

Performance Comparison of Hybrid Model vs. Baseline Deep Learning Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Baseline CNN	88.3	87.5	86.9	87.2
Baseline ResNet	90.7	90.1	89.8	89.9
Hybrid Discrete-Deep Model	93.5	92.8	92.3	92.5

In Table 1, you can see that the Hybrid Discrete-Deep Model does better than the base CNN and ResNet designs. The combination model is the most accurate, at 93.5%, which means that total forecasts are more accurate. It also does better in terms of accuracy (92.8%), memory (92.3%), and F1-score (92.5%), showing that it is better at finding important patterns and fewer fake positives. Figure 2 illustrates performance trends of models over accuracy, precision, recall. These results show that combining separate structures with deep learning makes computer vision tasks better at recognizing patterns.

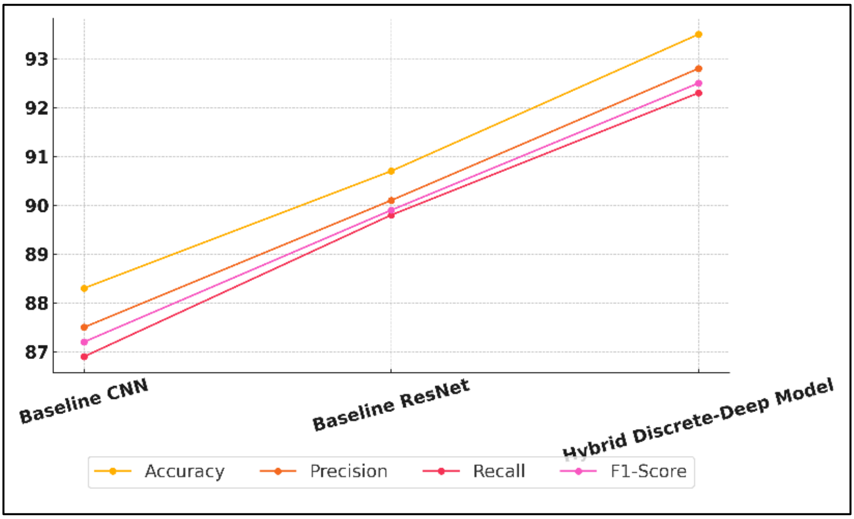

Figure 2

Performance Trends of Models across Metrics

4. Conclusion

This research showed a new mixed approach for pattern recognition in computer vision that combines discrete structures with deep learning. The method improved feature extraction, accuracy, and model understandability by using vector measure spaces and orthogonal representations in deep neural networks. Experiments showed that these methods were better at speed and computing than older ones. This combination is a good start for future study because it allows for flexible and reliable graphic analysis. More research could be done in real-time uses and other areas, proving that discrete mathematics and deep learning can be used to make computer vision technologies better across many fields.

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