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**Optimization CNN Architecture for Dog vs Cat Classification**

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# 1.Introduction to the selected problem :

* **The project addresses the challenge of binary image classification between dogs and cats using Convolutional Neural Networks (CNNs)The key innovation lies in utilizing Particle Swarm Optimization (PSO) to automatically discover optimal CNN architectures and hyperparameters, rather than relying on manual design.**

# 2. Problem Objectives :

* **Develop a robust CNN architecture for dog/cat image classification**
* **Optimize the network architecture and hyperparameters automatically**
* **Achieve higher accuracy and better generalization compared to manually designed architectures**
* **Provide a user-friendly interface for model deployment and comparison**

# 3.Mathematical Modeling :

3.1 Objective Function

* **The optimization problem is formulated as minimizing the negative validation accuracy:**

**Min θ −Accuracyval (θ)**

* **where θ represents the set of hyperparameters:**
* **Number of convolutional layers (n)**
* **Filter counts for each layer (f₁, f₂, ..., fₙ)**
* **Kernel sizes (k₁, k₂, ..., kₙ)**
* **Fully connected layer neurons (h₁, h₂, h₃)**
* **Learning rate (α)**
* **Weight decay (λ)**
* **Label smoothing (ε)**

# 3.2 Constraints :

* **The optimization is subject to the following constraints:**
* **Layer constraints :  
   3≤*n*≤20**
* **Filter count constraints:**

**3≤fi≤256, ∀i∈{1,...,n}**

* **Kernel size constraints:**

**3≤ki≤7, ∀i∈{1,...,n}**

* **Fully connected layer constraints:**

**1≤hi≤300, ∀i∈{1,2,3}1**

* **Learning rate constraints:**

**0.0001≤α≤0.001**

* **Weight decay constraints:**

**10−5≤λ≤10−3**

* **Label smoothing constraints:**

**0.0≤~~ε~~≤0.2**

4.Optimization Method: Particle Swarm Optimizatio(PSO)   
  
**1.Particle Structure** :

* **Each particle represents a complete CNN architecture configuration**
* **47-dimensional search space (1 + 20 + 20 + 3 + 3 parameters)**

**2.PSO Parameters:**

* **Swarm size: 20 particles**
* **Maximum iterations: 10**
* **Cognitive parameter (p): 0.5**
* **Social parameter (g): 0.5**

**3.Fitness Evaluation:**

* **Quick evaluation using 1 epoch training**
* **Validation accuracy as fitness metric**
* **Negative accuracy used for minimization**

**4.Dynamic Architecture Adaptation:**

* **Automatic adjustment of layer count based on input size**
* **Dynamic convolution capabilities for adaptive feature extraction**

5 Results and Interpretation :  
 **1.The optimization process produces:**

* **Architectural Outcomes:**
* **Optimized number of convolutional layers**
* **Optimized filter counts per layer**
* **Optimized kernel sizes**
* **Optimized fully connected layer configurations**

**2.Training Parameters:**

* **Optimized learning rate**
* **Optimized weight decay**
* **Optimized label smoothing**

**3.Model Components:**

* **Dynamic convolution layers for adaptive feature extraction**
* **Batch normalization for training stability**
* **Dropout (fixed at 0.5) for regularization**
* **Learning rate scheduling for optimization control**

6 Discussion :

**Current Strengths**

* **Automated architecture discovery**
* **Dynamic convolution capabilities**
  + - **Comprehensive hyperparameter optimization**
* **User-friendly interface for deployment**

## Potential Improvements :

**1.Extended Search Space:**

* + - **Include activation function selection**
    - **Optimize dropout rates**
    - **Consider different pooling strategies**

1. **Optimization Process:**

* **Implement multi-objective optimization**
* **Consider computational efficiency metrics**
* **Add early stopping criteria**

1. **Architecture Enhancements:**

* **Investigate residual connections**
* **Add attention mechanisms**
* **Explore model compression techniques**

7 Conclusion :

**The project successfully demonstrates the effectiveness of PSO in optimizing CNN architectures for image classification. The automated approach eliminates the need for manual architecture design while potentially achieving .**

7.2 References :

* <https://cys.cic.ipn.mx/ojs/index.php/CyS/article/viewFile/5512/3887>
* <https://www.mdpi.com/2073-8994/14/11/2323>
* [**(PDF) Particle swarm optimization of deep neural networks architectures for image classification**](https://www.researchgate.net/publication/333546501_Particle_swarm_optimization_of_deep_neural_networks_architectures_for_image_classification)