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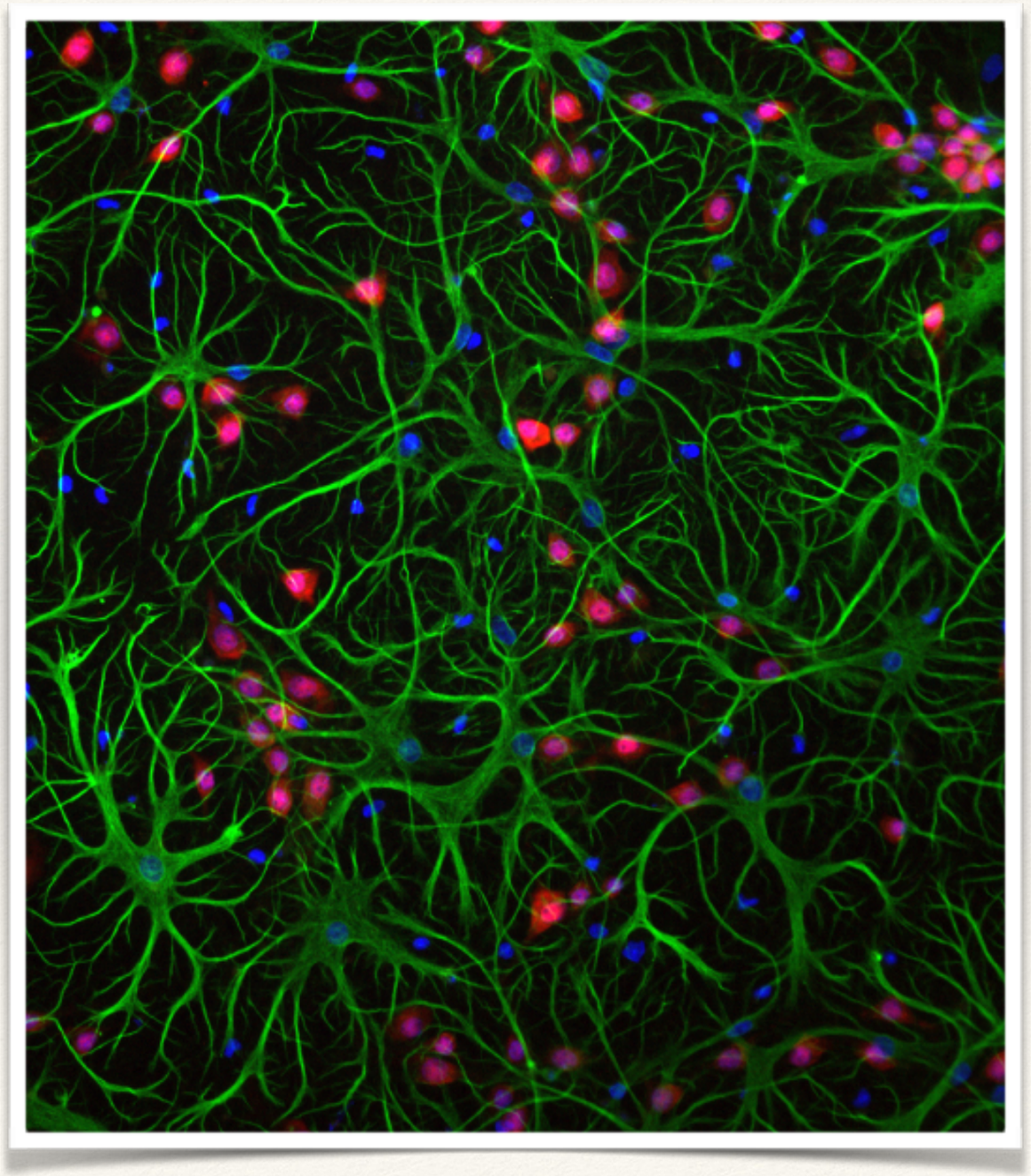
Evolutionary Artificial Neural Networks

An Application to Facial Recognition Software

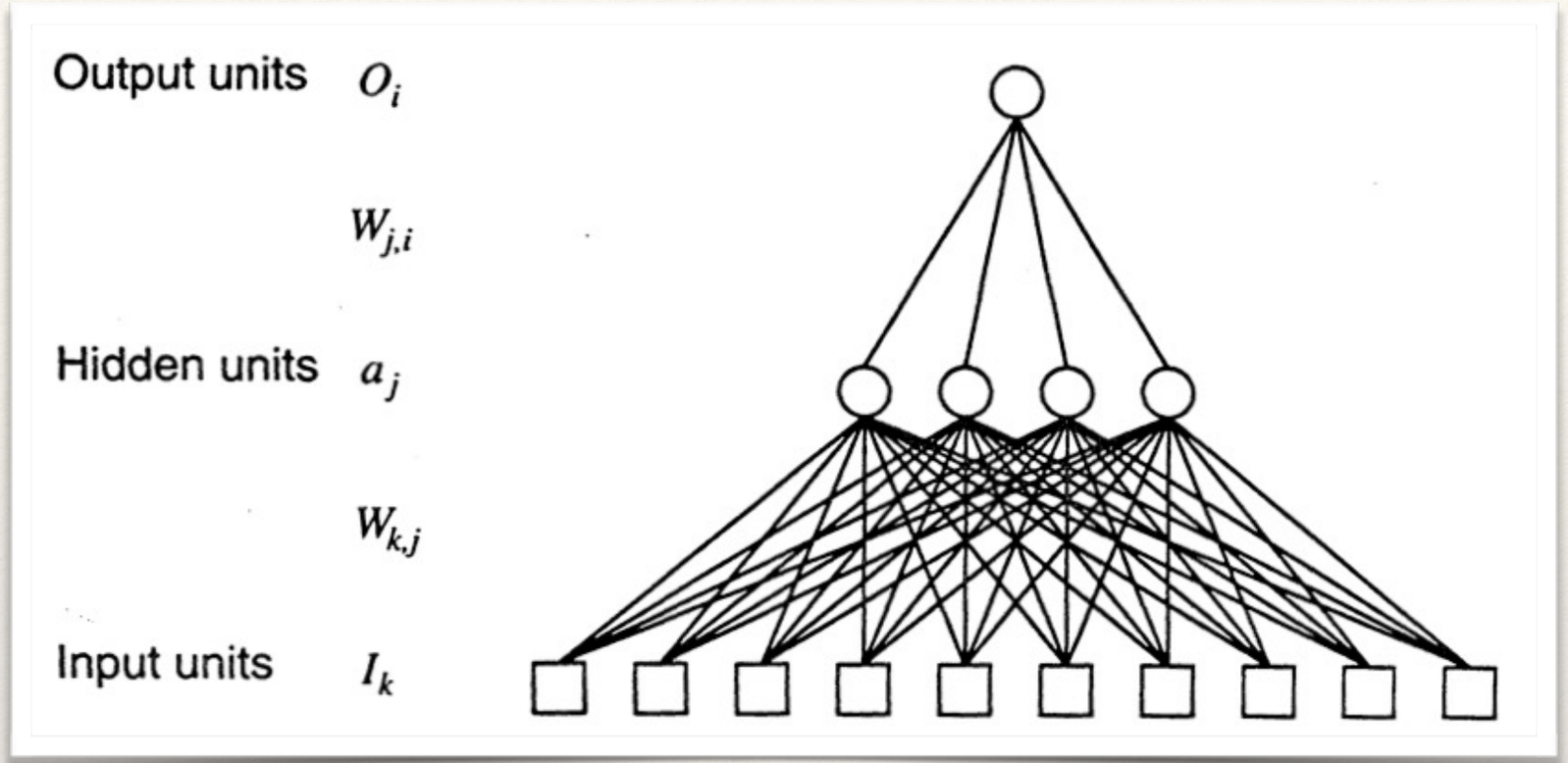
Computer Science 3445: Nature Inspired Computation

Motivation and Background

- Brain architecture is constantly changing with respect to topological connections between neurons.
- This changing, i.e. Neuroplasticity, can be conceptualized as inter-neural connections' evolution.



Artificial Neural Networks (ANN)



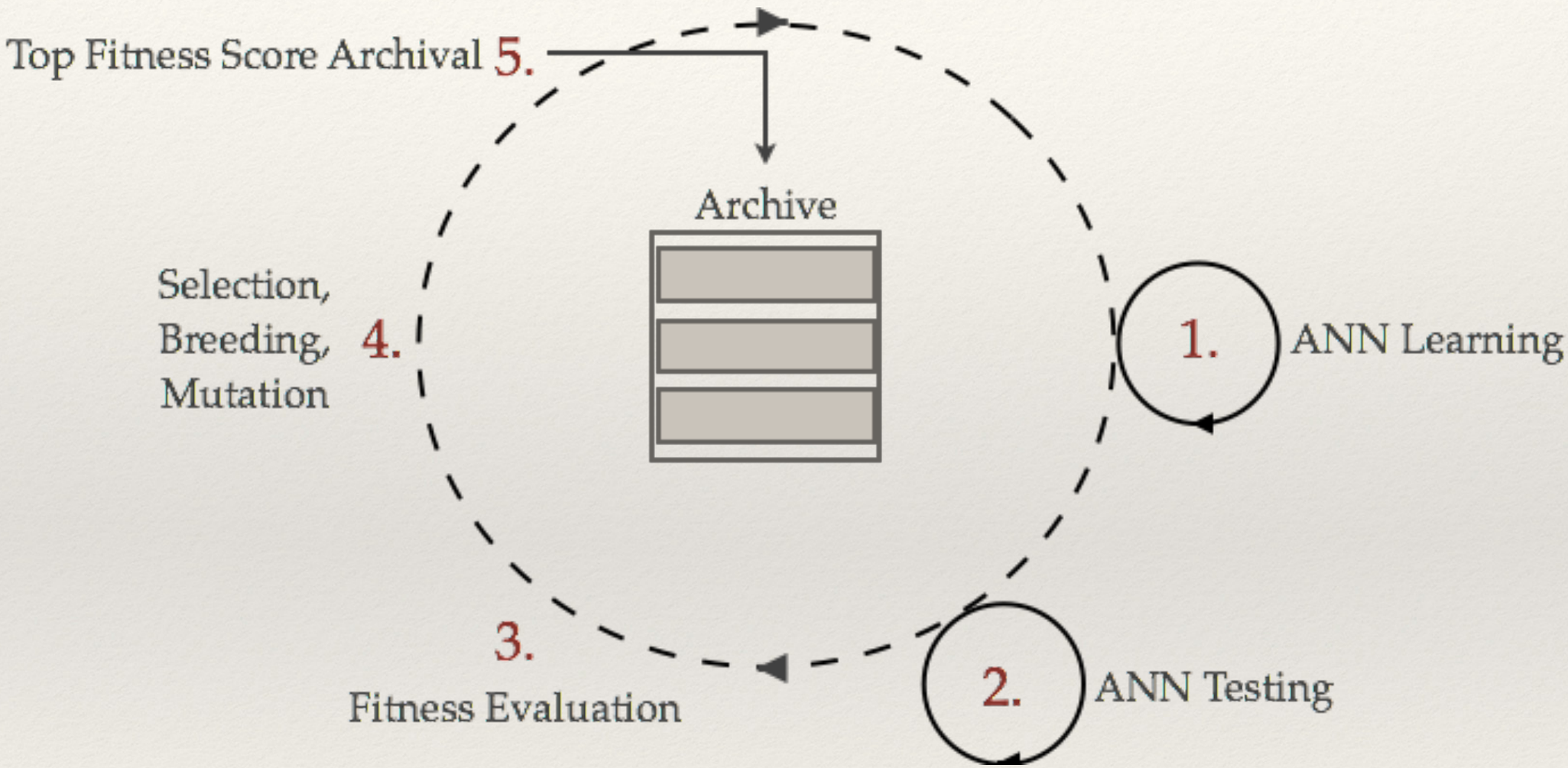
- **Figure 1**: a typical multilayered feed-forward neural network

$$W_{j,i} \leftarrow W_{j,i} + (\alpha \times a_j \times Err_i \times g'(in_i))$$

$$W_{k,j} \leftarrow W_{k,j} + (\alpha \times I_k \times \sum_i W_{j,i} Err_i \; g'(in_i) \; g'(in_j))$$

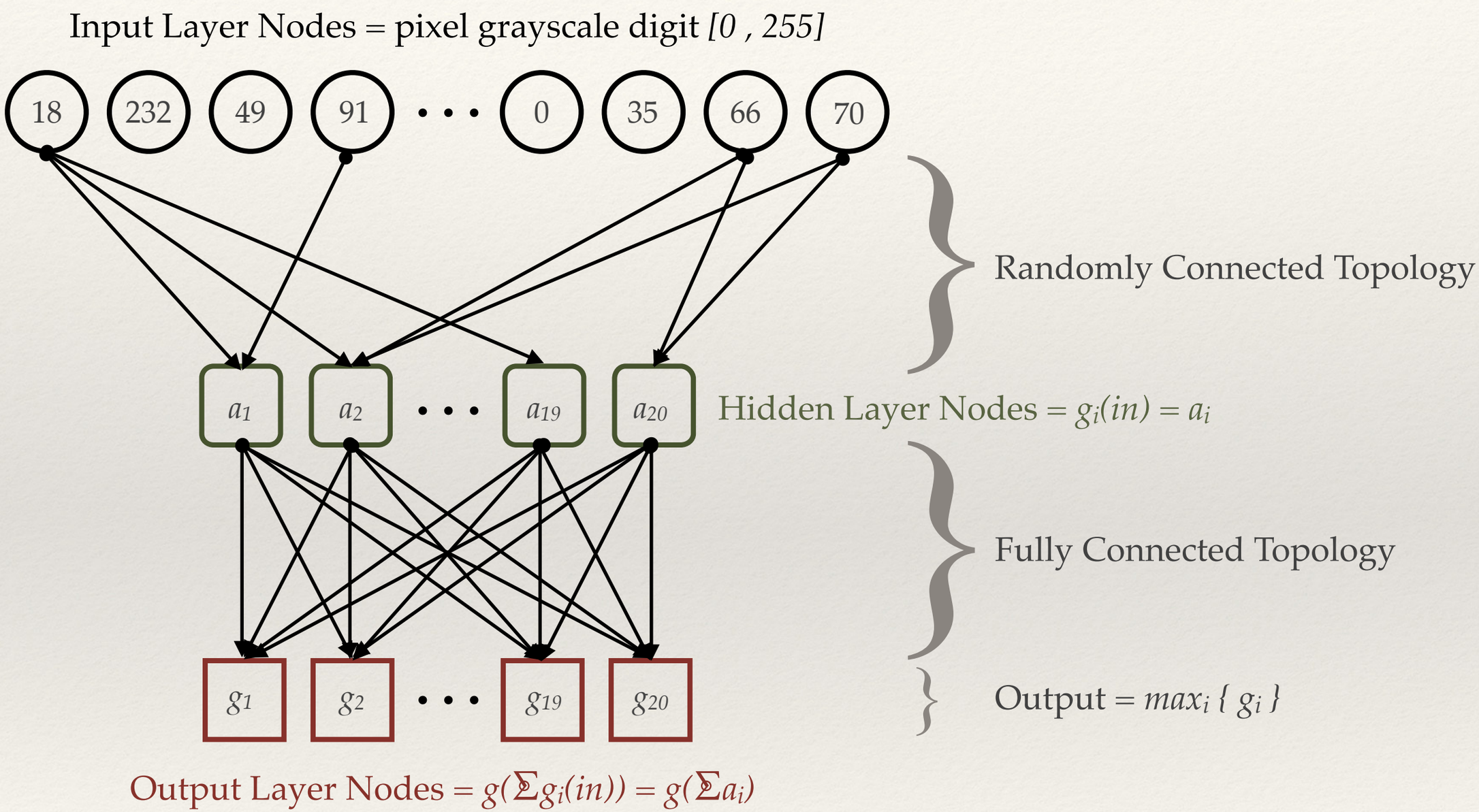
- **Figure 2**: *(top)* Hidden-to-Output Node Edge-weight update. *(bottom)* Input-to-Hidden Edge-weight update.

Evolutionary Artificial Neural Networks (EANN)



- **Figure 3:** the algorithm used to evolve a population of ANN topologies. Note that for this EANN, only the topologies between the input node layer and hidden node layer are evolved with the GA.

Application to Facial Recognition



- **Figure 4:** The conceptualization of the facial recognition EANN.

Application to Facial Recognition

- **Note:** for this research, the fitness function used is:

$$\Phi(a) = PCC_a^{(t)}(D_{test})$$

where:

$\Phi(a)$ is the scalar fitness value for individual a.

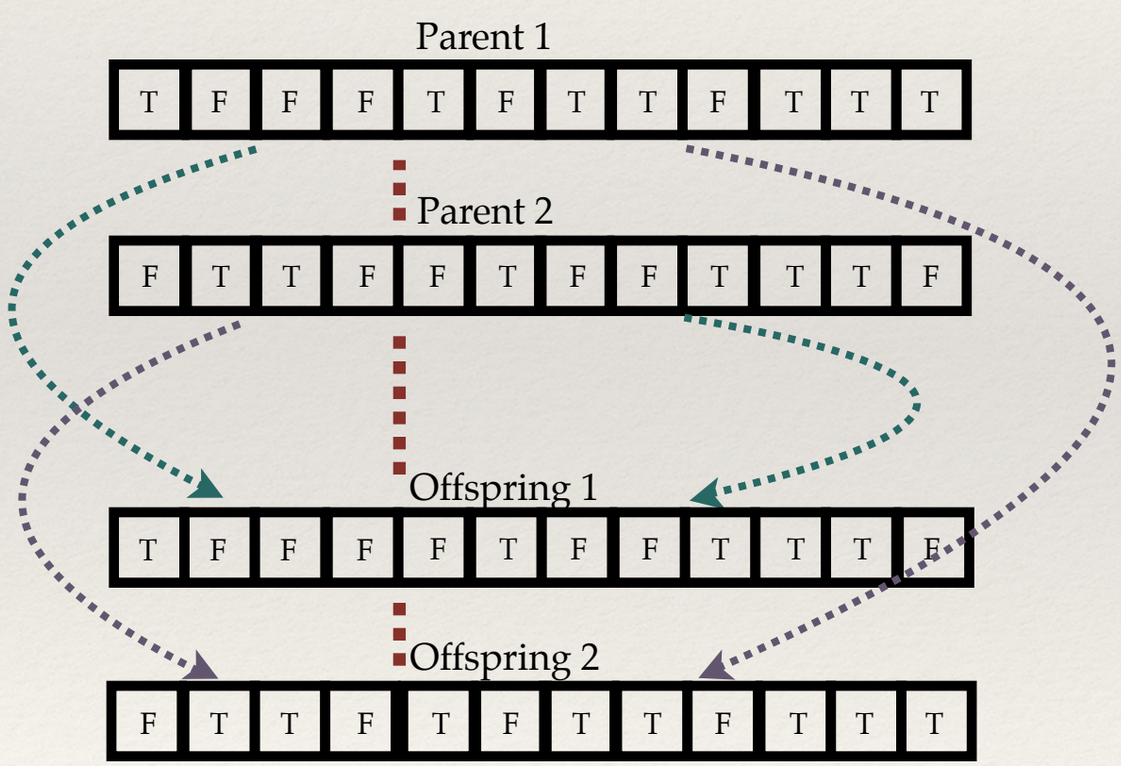
$PCC_a^{(t)}$ is Percentage of Clauses Satisfied for input node a at generation t.

D_{test} is the test value set.

Application to Facial Recognition

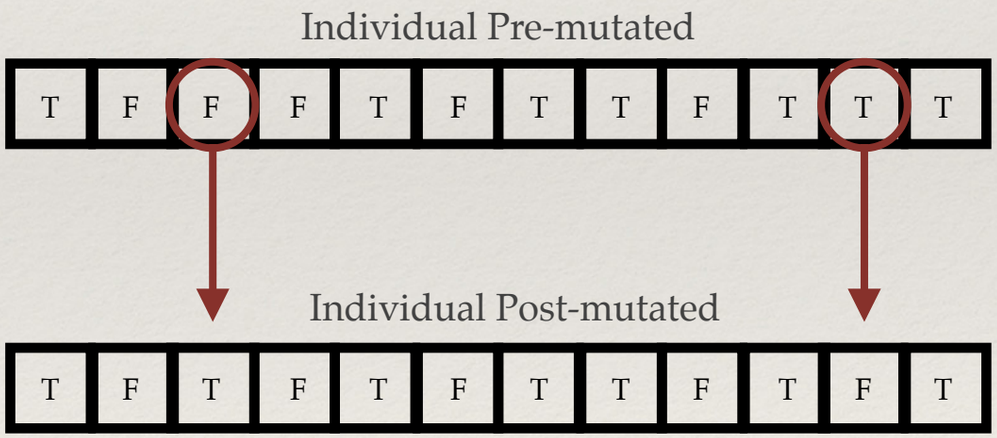
- **Note:** for this research, the breeding and mutation operations are as follows:

Breeding



- **Figure 5:** One Point Crossover (OPC) on a given input nodes' connection to the Hidden Node Layer

Mutation



- **Figure 6:** Mutation on a given input nodes' connection to the Hidden Node Layer

Problem Files

- 20 individuals photographed, 32 photos per individual: **640** total

Resolutions: { (128 x 120), (64 x 60), (32 x 30) }

*Orientations: { (left), (right), (up), (down) }***

Expressions: { (neutral), (happy), (angry), (sad) }

Eye-State: { (sunglasses on), (sunglasses off) }

- **Figure 7:** a sample of four images of one individual showing various permutations.

Experimental Methods

ANN Tests

- **Measurements**:
  1. Training Progression
  2. Overall Percentage Satisfied
  3. Runtime per Test
- **Parameters Involved:**
  1. Epochs: *{25, 50, 75, 100}*
  2. Learning Rate: *{.2, .3}*

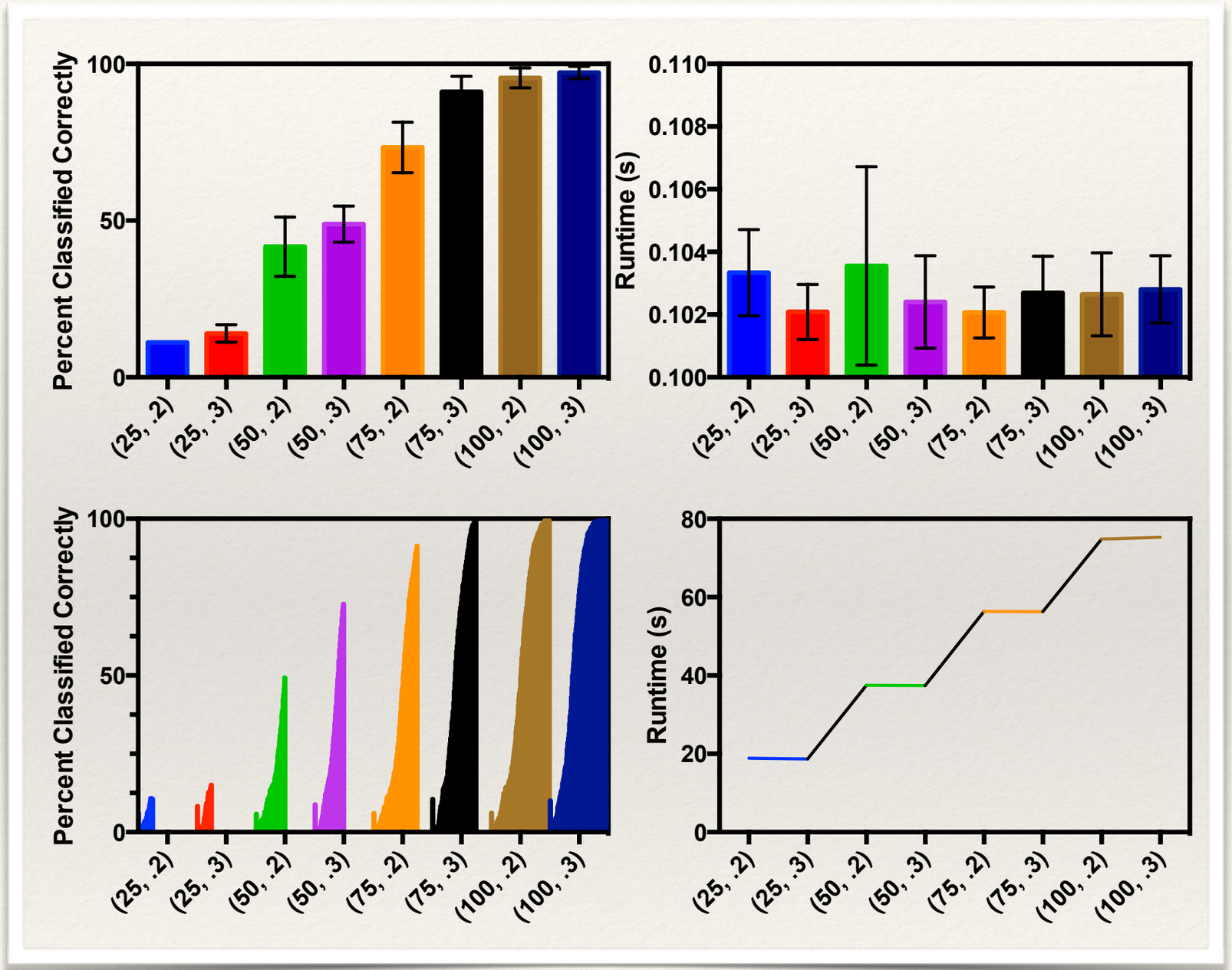
EANN Tests

- **Measurements**:
  1. Overall Optimal Solution per Generation
  2. Runtime per Test, Runtime per Generation, Runtime per Generation per Individual
  3. Training Progression per Generation per Individual
- **Parameters Involved:**
  1. Epochs: *50*
  2. Learning Rate: *{.2, .3}*
  3. Population Size: *8*
  4. Generations: *5*
  5. Selection Method: *Boltzmann Selection*
  6. Breeding Method: *One Point Crossover*
  7. Crossover Probability: *{.5, .7}*
  8. Mutation Probability: *{.01, .1}*

Results: Fully Connected ANN

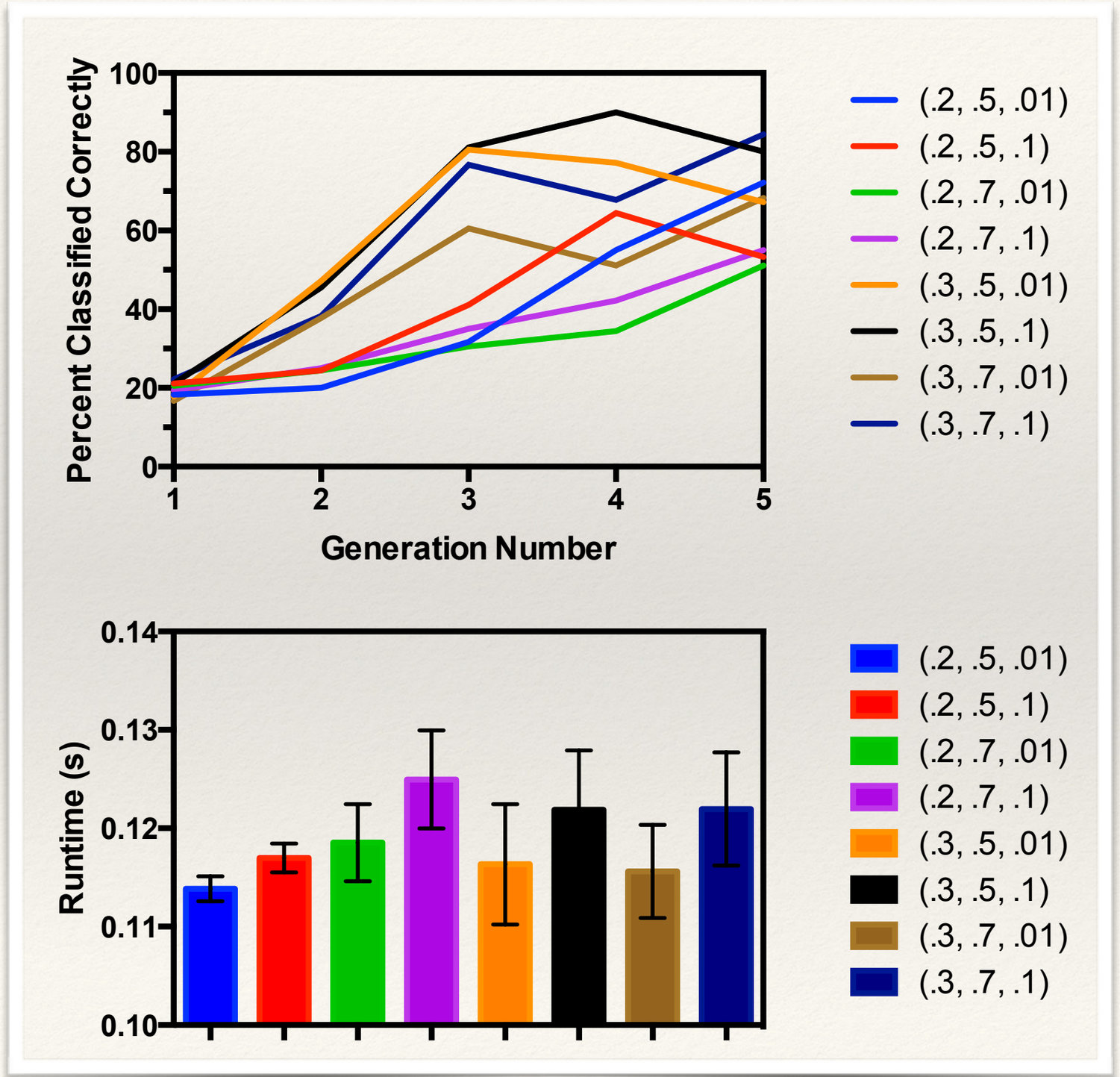
Testing Data:

Training Data:



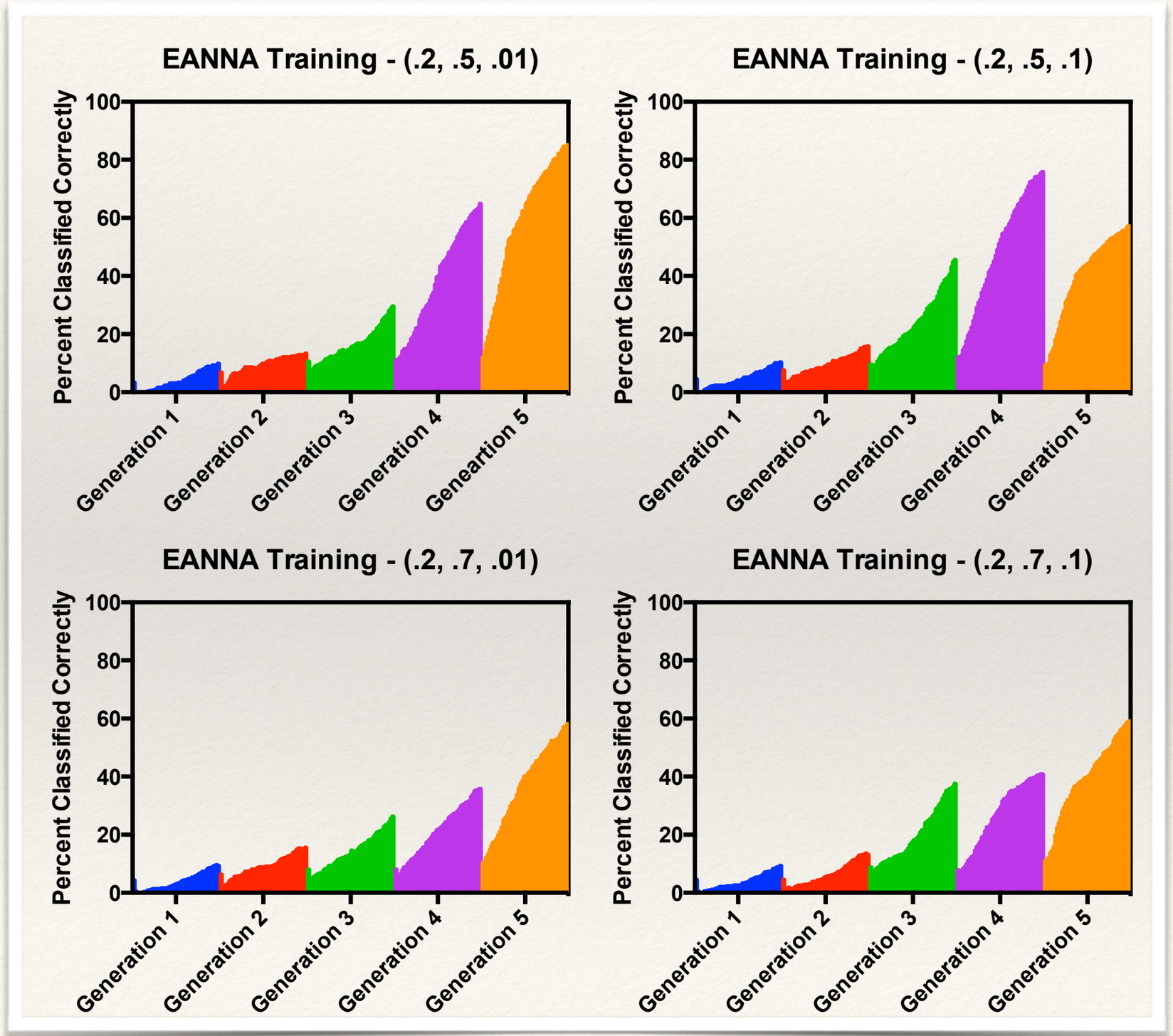
- **Figure 8:** A comparison of all tests run on an un-evolved ANN.

Results: EANNA Testing



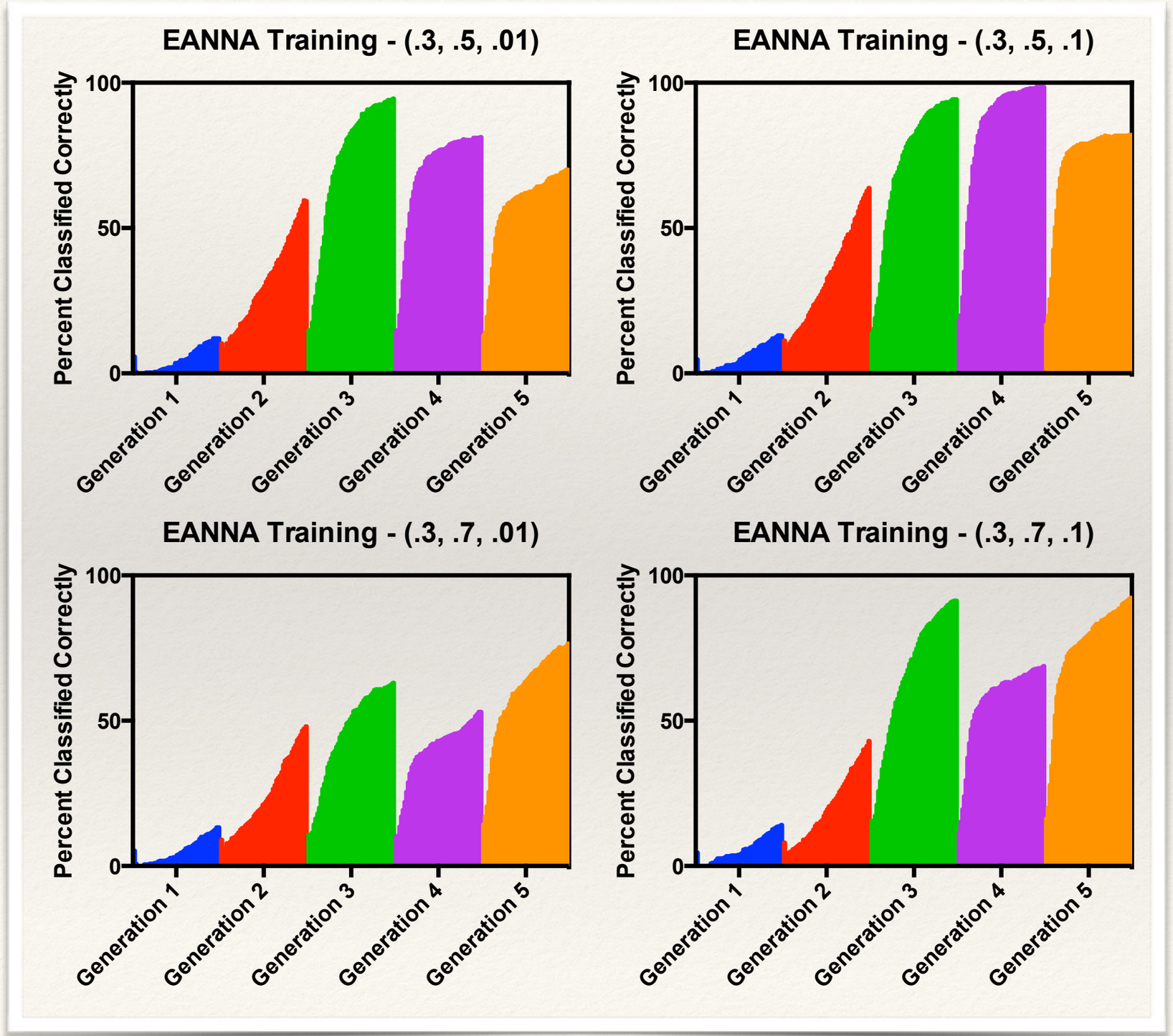
- **Figure 9**: A comparison of the testing results of the EANNA

Results: EANNA Training (1 of 2)



- **Figure 10:** A comparison of (½) of the permutations of the EANNA during the training.

Results: EANNA Training (2 of 2)



- **Figure 11:** A comparison of the other (½) of the permutations of the EANNA during the training.

Conclusions

1. For a set number of epochs and generations, **EANNA outperforms ANNA** with respect to correctly satisfied images.
2. ANNA has a faster runtime.
3. The optimal parameter variation after five generations for EANNA was: *(.3, .7, .1)*
4. The global best parameter variation over all generations for EANNA was: *(.3, .5, .1)*

Future Directions

- A wider exploration into the parameter space. This includes:
  1. Connection Probability in EANNA
  2. The number of epochs in EANNA
  3. Learning Rate
  4. Crossover Probability and Type in EANNA
  5. Mutation Probability in EANNA
  6. Selection Method in EANNA
  7. Population Size
  8. Number of Generations

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