Sistemas Inteligentes Híbridos

Improving Image Classification Accuracy using Hybrid Systems of Support Vector Machines and Convolutional Neural Networks

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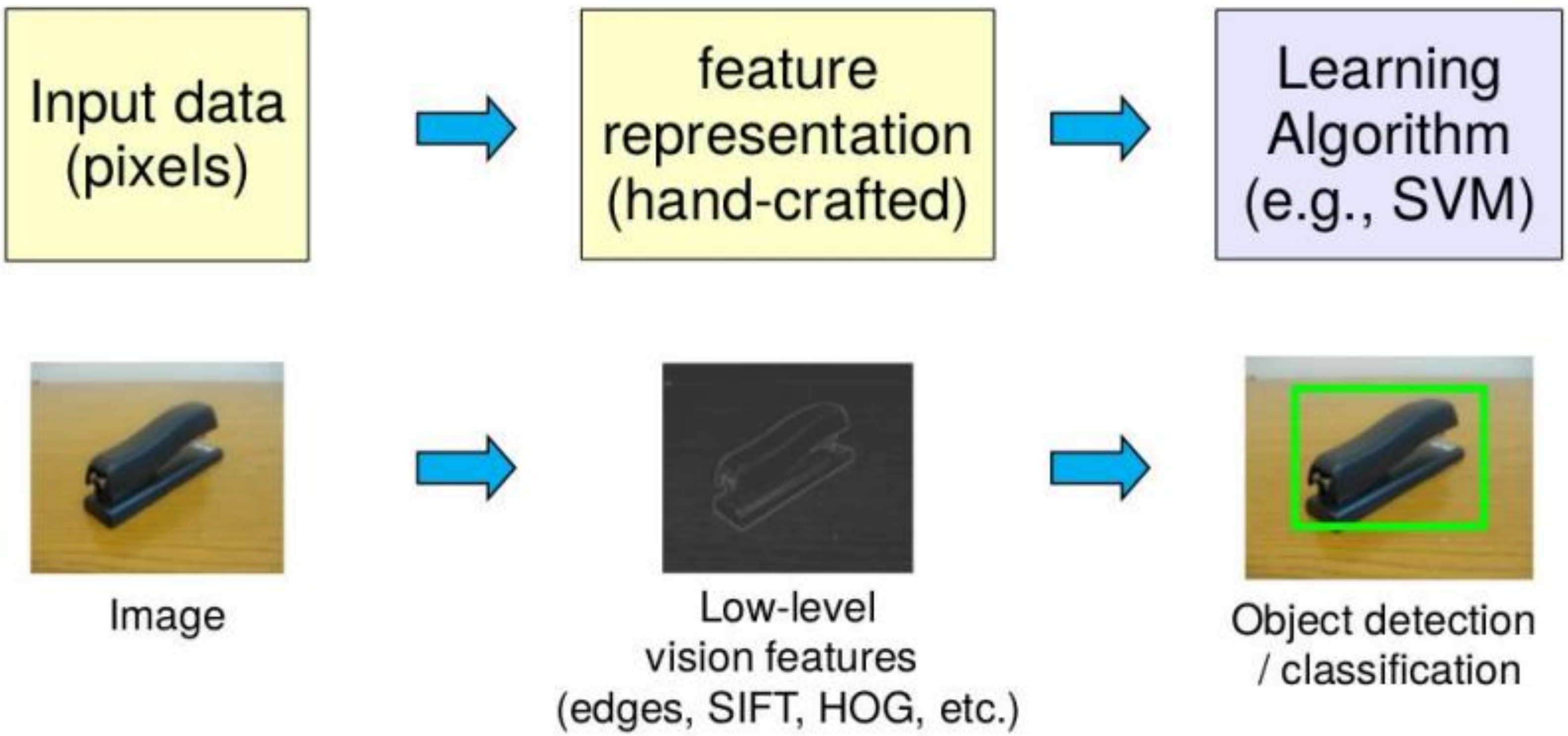
Motivation

- Present the limitations of SVMs (more generally, of shallow architectures) and CNNs

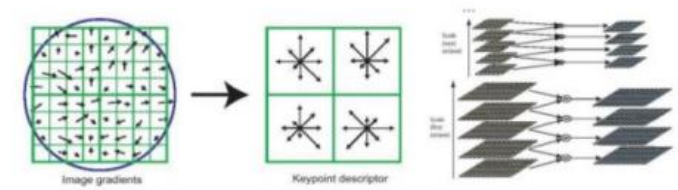
- Show that a Hybrid Systems combining SVMs and CNNs can achieve a better test accuracy than both original system components

Support Vector Machines

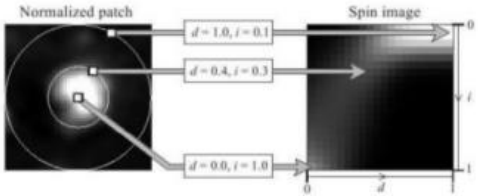


Support Vector Machines

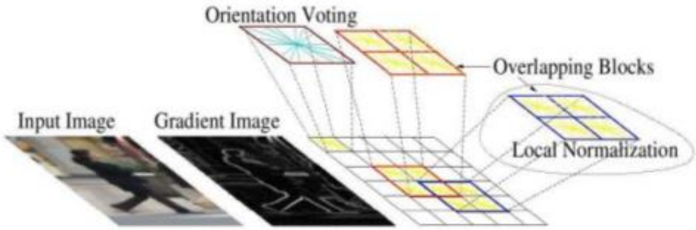
Computer vision features



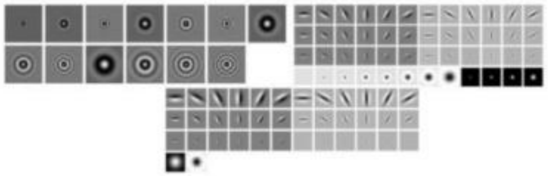
SIFT



Spin image



HoG



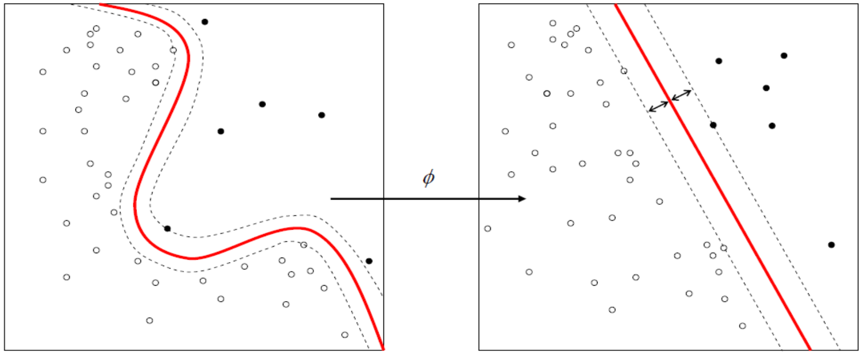
Textons

and many others:

SURF, MSER, LBP, Color-SIFT, Color histogram, GLOH, …..

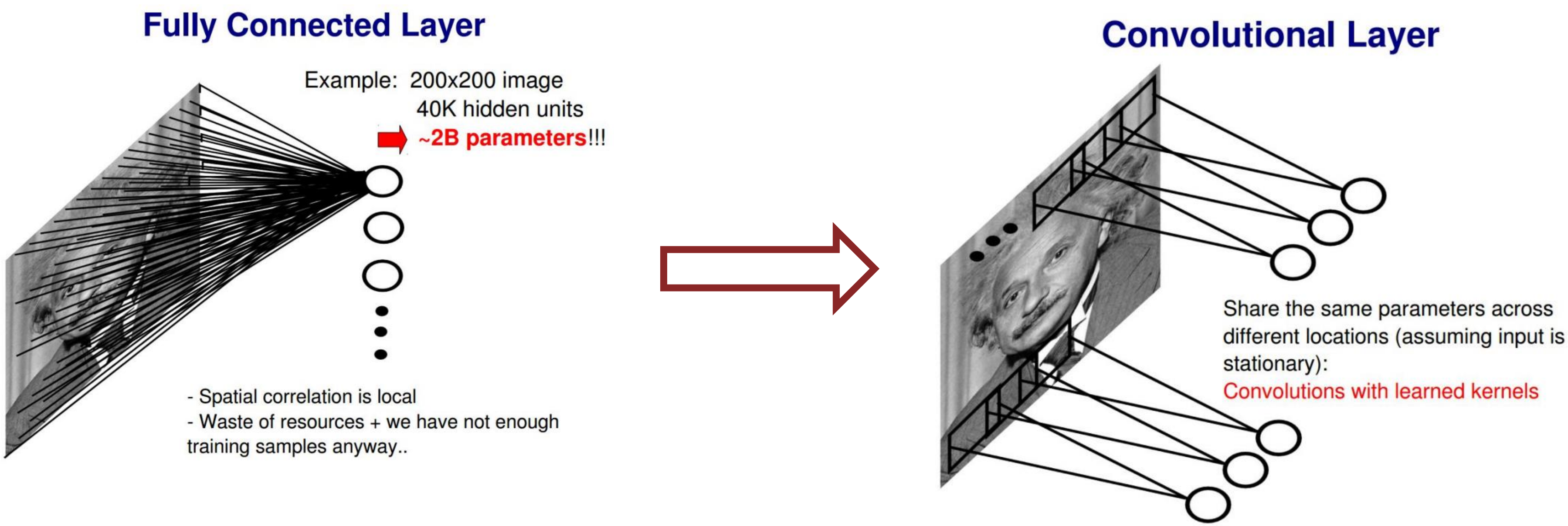
Support Vector Machines

- Maximum Margin Classifiers
- Empirical Risk Minimization
- Convex Optimization
- Shallow Architecture
- Feature Engineering



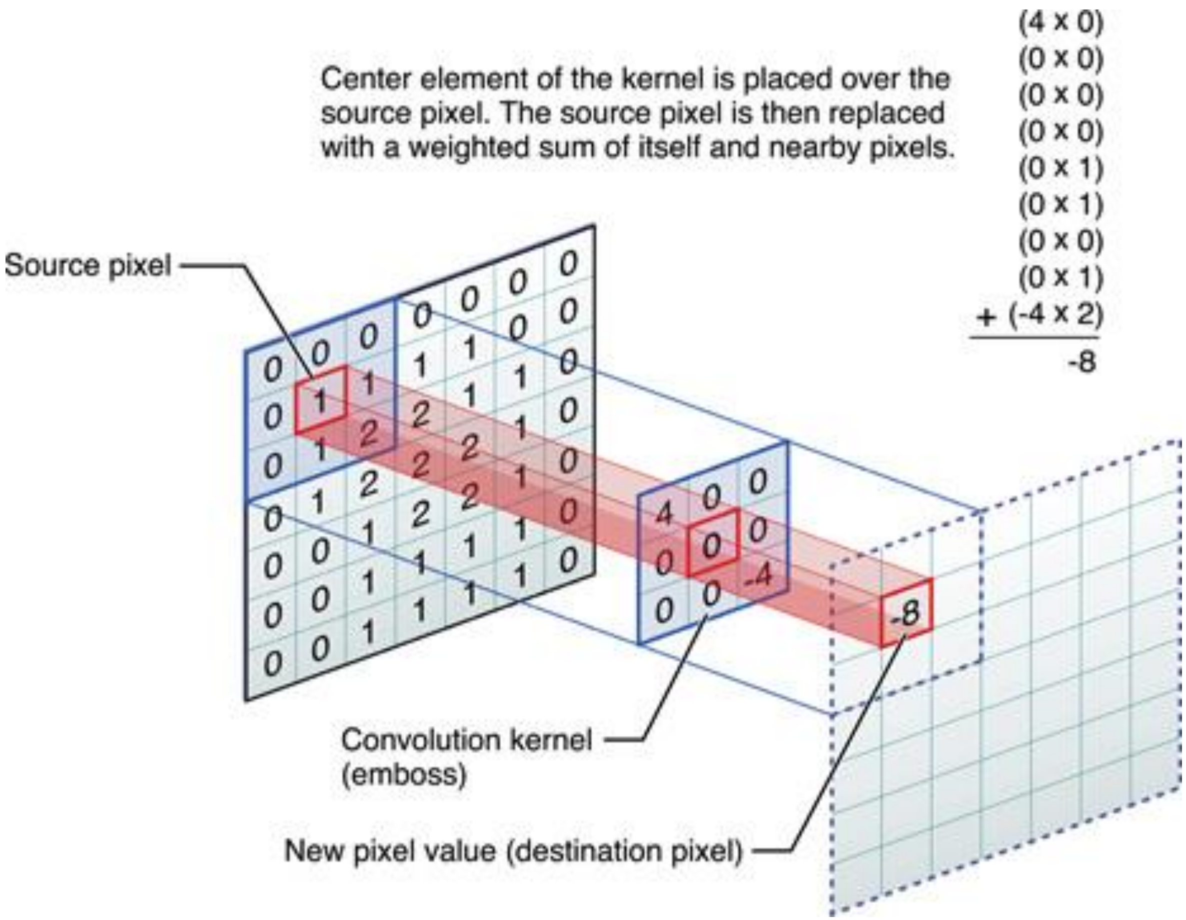
Good classifier, but do not learn deeper features from data

Convolutional Neural Networks

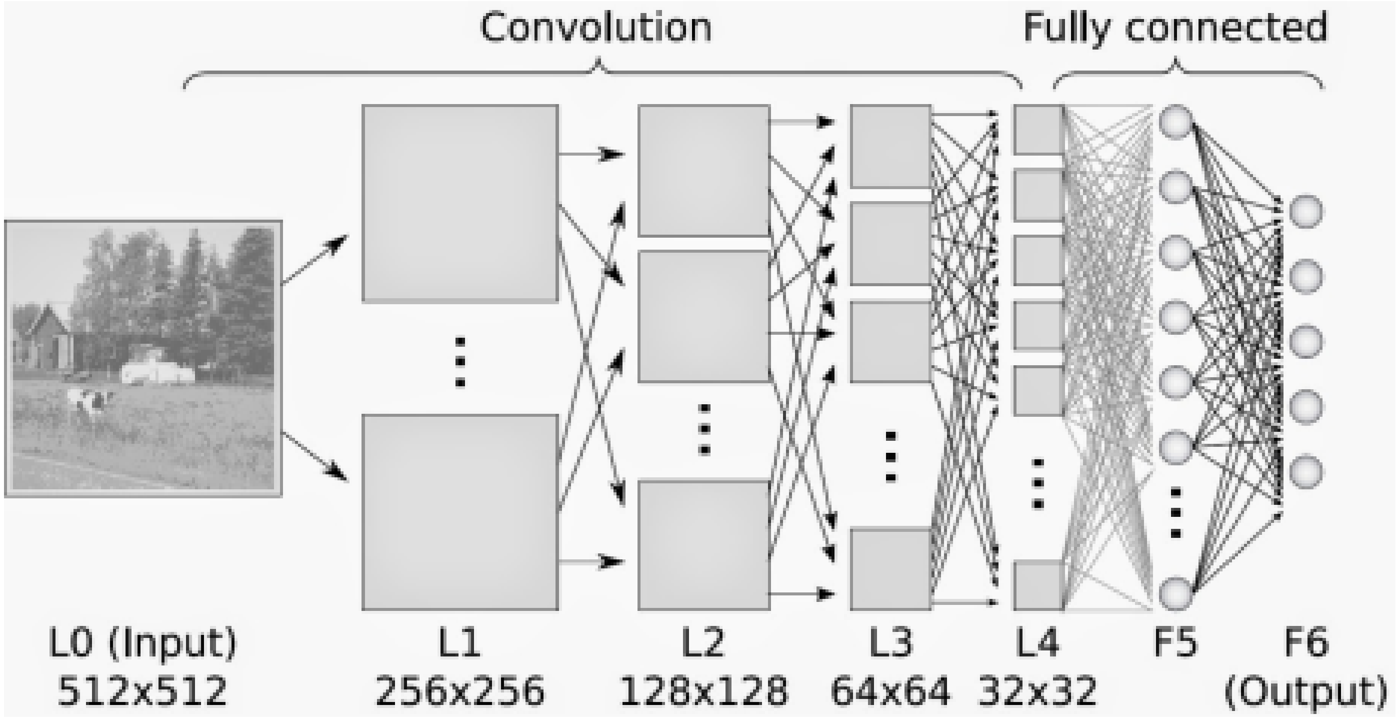


Receptive Fields, Weight Sharing and Translational Symmetry: Feature Learning

Convolutional Neural Networks

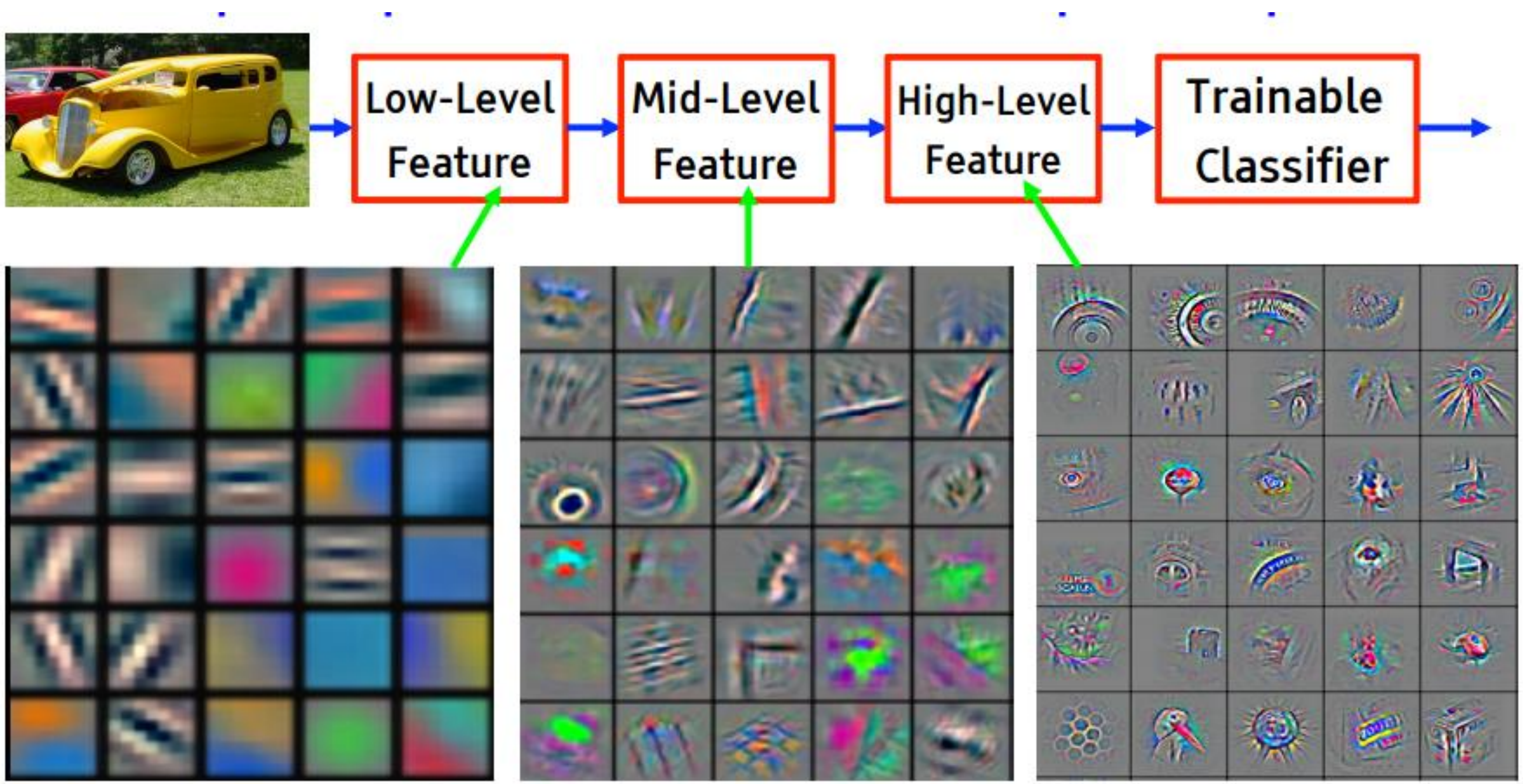


Convolutional Neural Networks



Compositional and Hierarchical Feature Learning Architecture

Convolutional Neural Networks



Convolutional Neural Networks

- Hierarchical and Compositional Feature Learn
- Very Scalable and Parallel Computation
- “Perceptron-Like” Full Connected Classifier
- Non-convex Optimization

Good learnable feature extractor, but not so good classifier

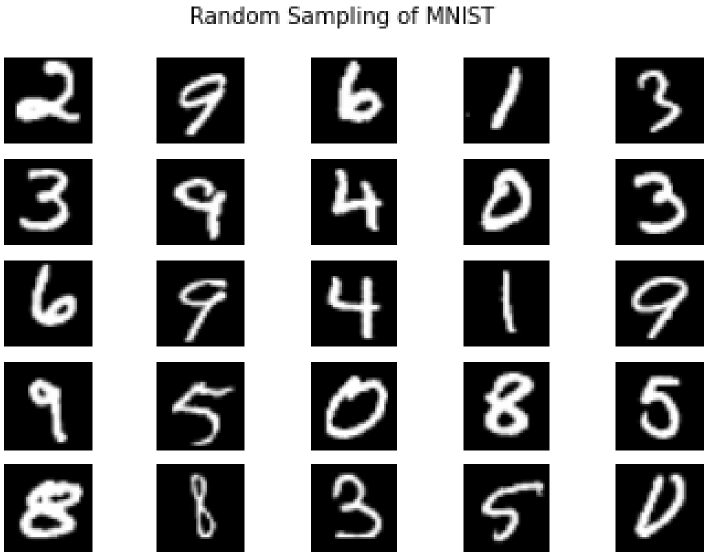
Proposed Hybrid System

- Train a Convolutional Neural Network (CNN)
- Remove the Last Full Connected Layer:
  Extract the Features Learned
- Classifier the SVM using the Learned Features

The hope is to use the best characteristic of each individual system in order to create the hybrid system

MNIST Dataset

- 28x28 Grayscale Images of Handwritten Digits
- Linearized 784 Features
- Training Set: 55.000 Examples
- Test Set: 10.000 Examples



Experiments: Models

- Linear Kernel SVM
- Gaussian Kernel SVM
- 1024 Nodes Extreme Learning Machine
- 4096 Nodes Extreme Learning Machine
- Convolutional Neural Network (CNN)
- SVM+CNN: The Hybrid Proposed System

Experiments: Models

- 5x5 Kernel Sizes in All Convolutional Layers
- The First Convolutional Layer = 32 Kernels
- The Second Convolutional Layer = 64 Filters
- The Third Layer = 128 Nodes Fully Connected
- The Fourth Layer = 10 Nodes Fully Connected

Experiments: Methods

- Each model were trained and tested when possible using a Graphics Processing Unit (GPU)
- **One hundred execution of training and test of each model was performed, with exception of SVM with Linear and Gaussian Kernels**
- **The extracted features are 128 higher level characteristics instead of the original 784 vector**

TABLE I
TEST PERCENT ACCURACY COMPARISON

Experiment	CNN	SVM_{CNN}
1	97.52	98.55
2	97.59	98.66
3	97.58	98.59
4	97.25	98.51
5	97.29	98.49
6	97.44	98.62
7	97.03	98.44
8	97.49	98.62
9	97.26	98.48
10	97.16	98.32

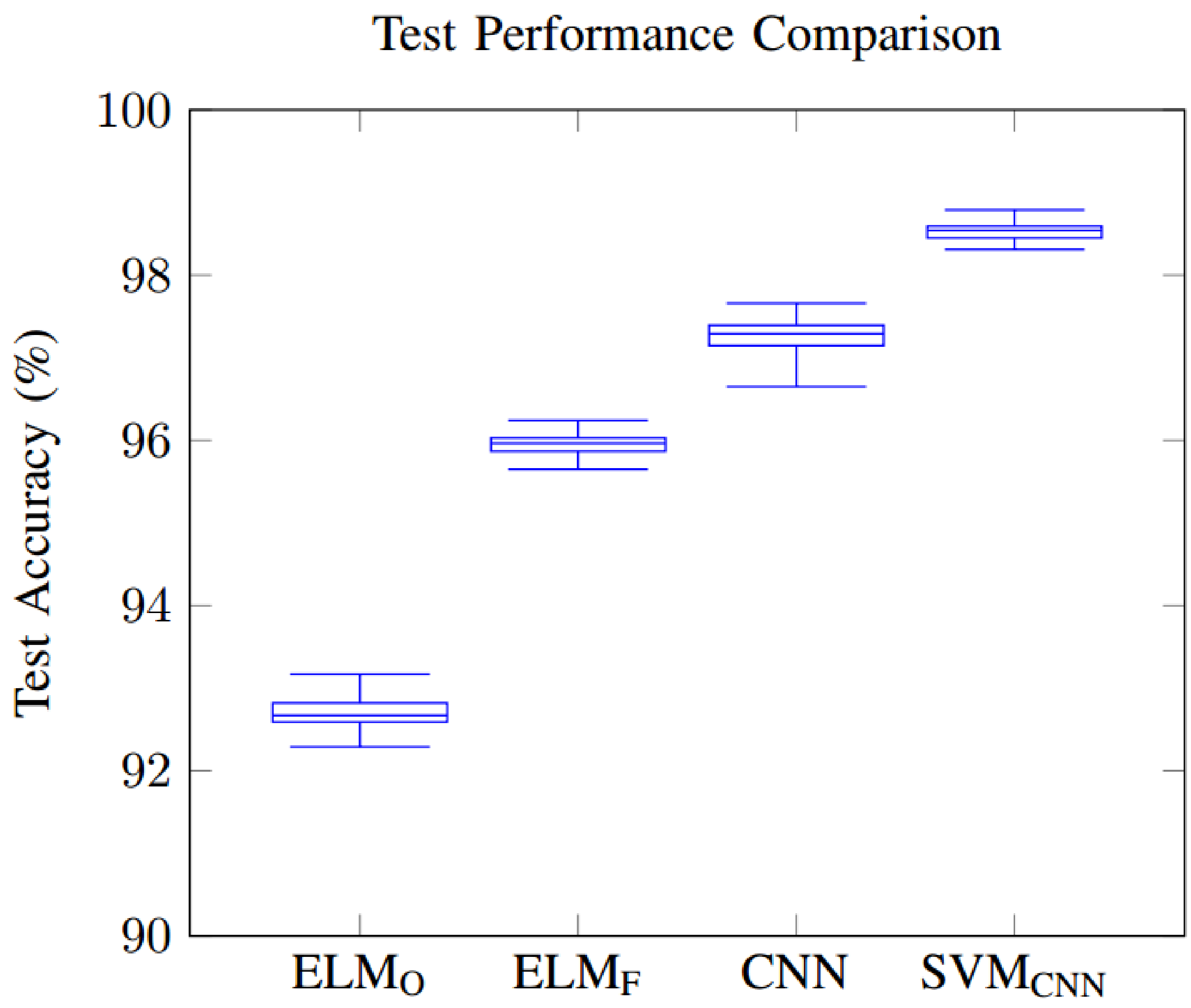


Fig. 1. Box plot of the distribution of test percent accuracy of one hundred of experiments of each model on MNIST data set.

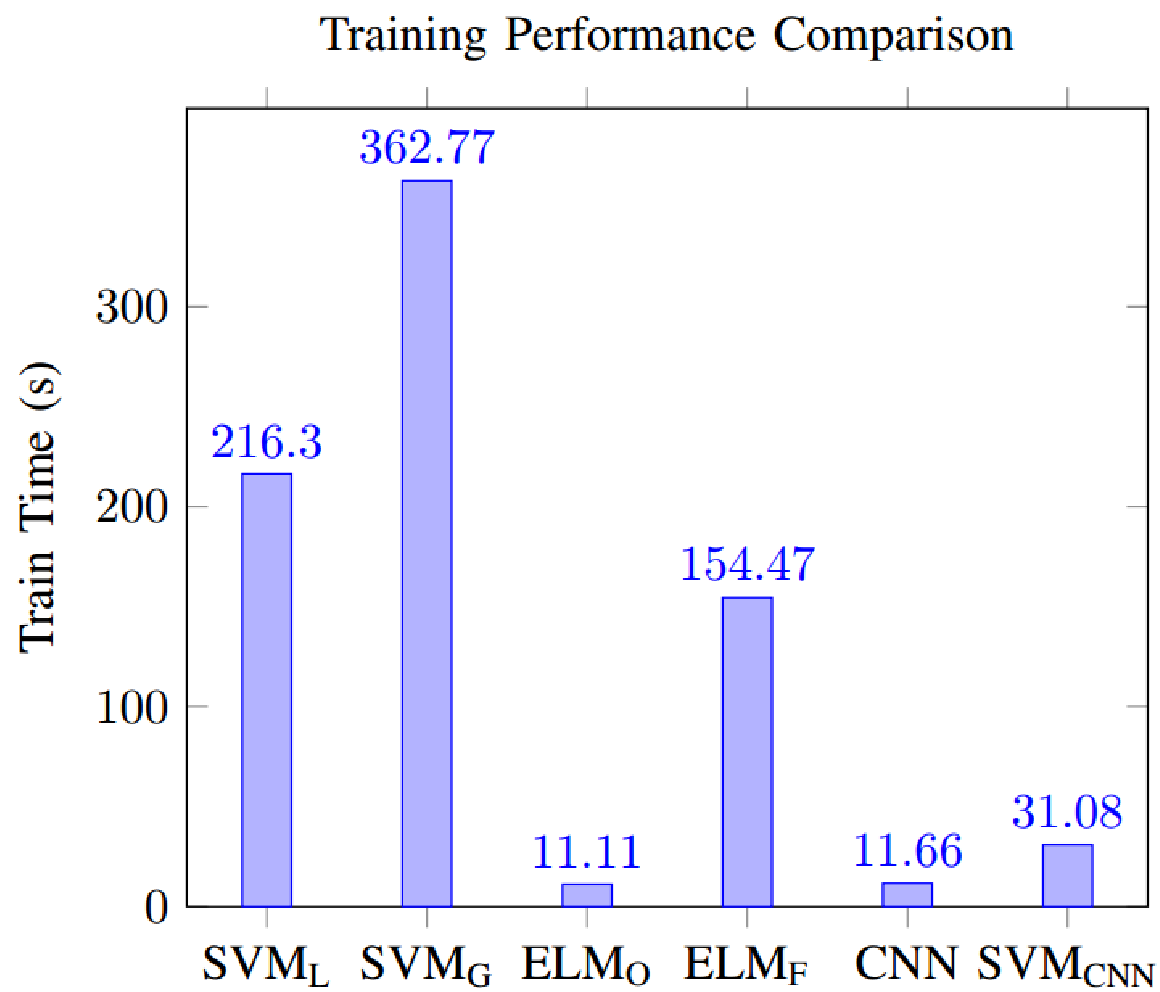


Fig. 2. Mean training time in seconds of one hundred of experiments of each model, with exception of SVM_L and SVM_G, that were executed just once since they have an almost deterministic training time.

Experiments: Models

- The proposed hybrid system achieves better test performance than both original systems
- The compound system presents much faster training time than the original SVM model
- The resultant system is very competitive when compared to state-of-art models

Software Tools

TensorFlow

scikit learn

python™

GitHub

https://github.com/dlmacedo/SVM-CNN

References

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