Detection of Wildfires with Artificial Neural Networks

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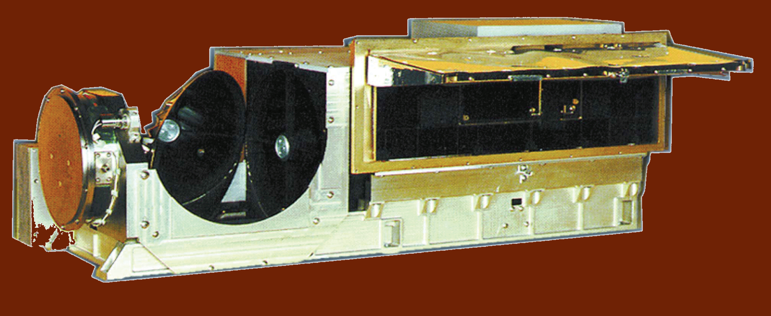

Introduction

Currently fire detection using satellites is accomplished with algorithms and human analysts. Artificial neural networks (ANNs) have been shown to be more accurate than algorithms or statistical methods for applications dealing with multiple datasets of complex observed data in the natural sciences.

This study utilized polar orbiter numerical data from the Advanced Very High Resolution Radiometer (AVHRR) in an attempt to determine how accurately a machine learning (neural network) approach can recognize wildfires via satellite imagery.

Workflow

- Make shapefile of known fire locations with ArcGIS
- Obtain satellite numerical data
- Guidance correct satellite data with ENVI
- Crop 10x10 pixel data blocks around fires, varying the location of the fire in the field of view.
- Crop 10x10 pixel no fire data blocks over various land/ocean features.
- Produce neural network input/output data files from the cropped data with Python script
- Run neural network in MATLAB for multiple datasets/network configurations.
- Analyze network output with Python scripts

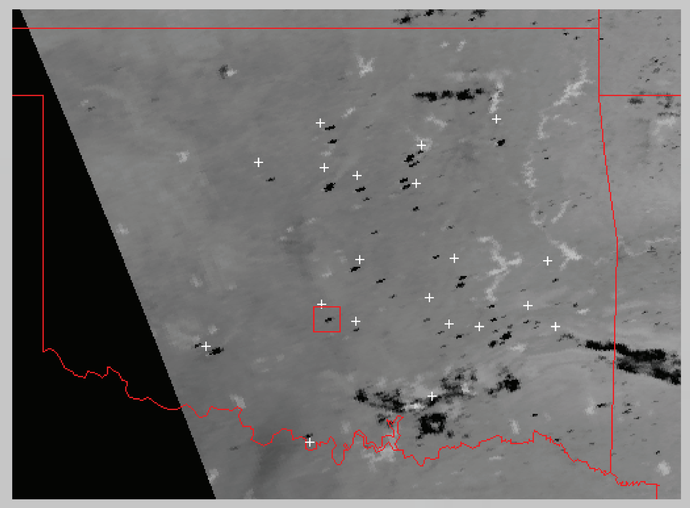

Fig.1 - January 29, 2011 Infrared (IR) image of fires covering the state of Oklahoma. White crosses denote major cities near fires reported by local media. These areas were near the edge of the field of view of the AVHRR, so pixel sizes are larger, but the fires are still easily detectable.

Neural Network Design

The neural network was designed with the MATLAB network pattern recognition tool (nprtool). The satellite image segments were 10x10x6, 100 pixels from each of 6 bands on the AVHRR instrument. The number of input neurons directly corresponded to how many channels of data were being utilized. The number of hidden layer neurons was varied from 5-350 in steps of 5 neurons. Each network configuration of input data and number of hidden layer neurons was run 10 times so a reasonable assessment of the overall network configuration could be achieved.

Approximately 4,200 runs of a pattern recognition network were completed and 30 parameters from the network recorded to characterize its performance. These parameters were plotted with various data display techniques to determine which network configuration was not only most accurate in fire classification, but also computationally efficient.

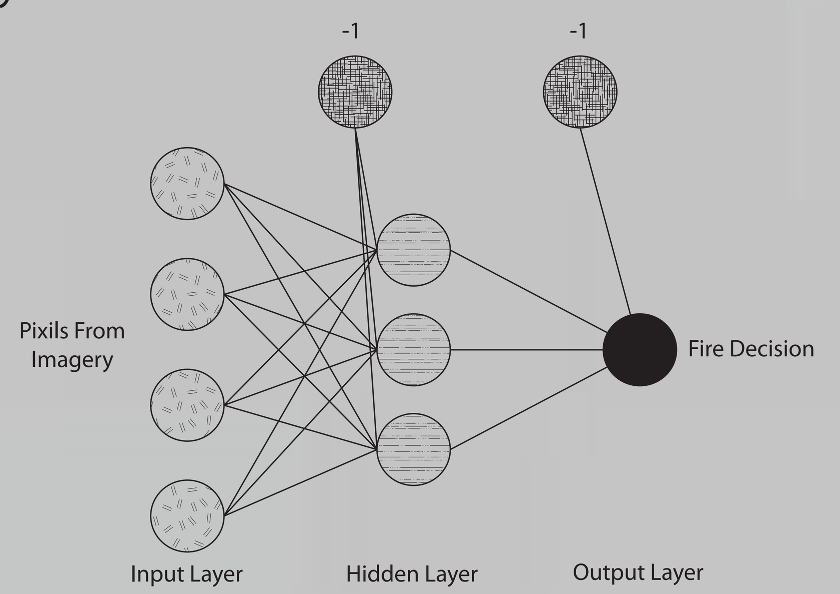

Fig.2 - Typical diagram of a basic neural network including bias (-1) nodes.

Network Parameters Summary

Number of Hidden Layer Neurons: *5-350*
Input Vector Components: *100-600*
Training Algorithm: *Scaled Conjugate Gradient*
Data Set Size: *Training 393, Validation 91, Testing121 (cases)*

Results

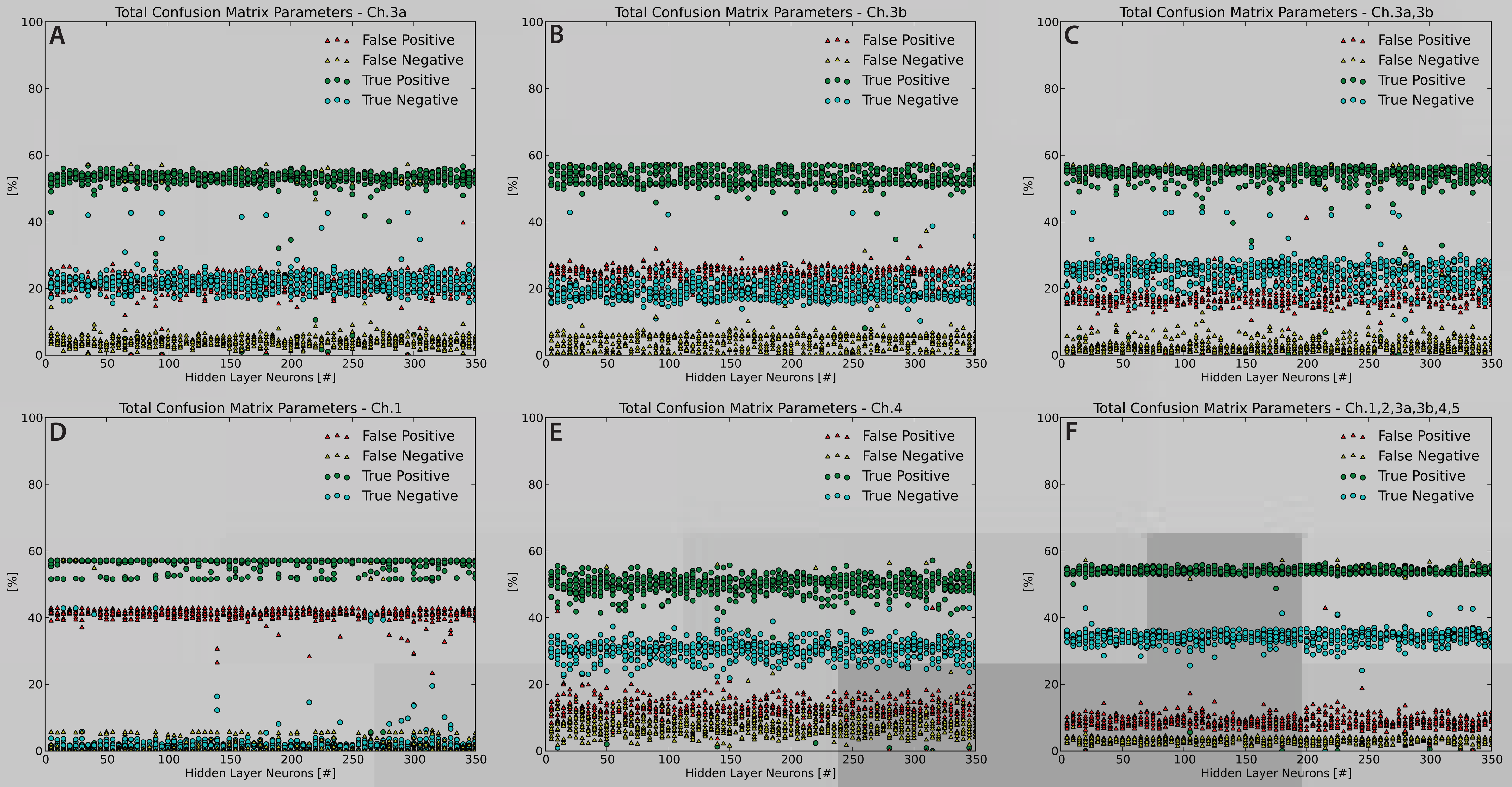

Fig. 3 - Plots of the four main performance parameters (false positive, false negative, true positive, true negative). The performance of channels 3a/3b (A/B) are similar, but the combination of the two (C) shows a reduction in scatter and a slightly raised true negative rate. Channel 1 (D) demonstrated a high false positive rate; channel 2 exhibited similar results. Channels 4 (E) and 5 (not shown) were better than channels 1 and 2 when determining true negatives. The lowest scatter and most desirable result was obtained with all 6 channels (F).

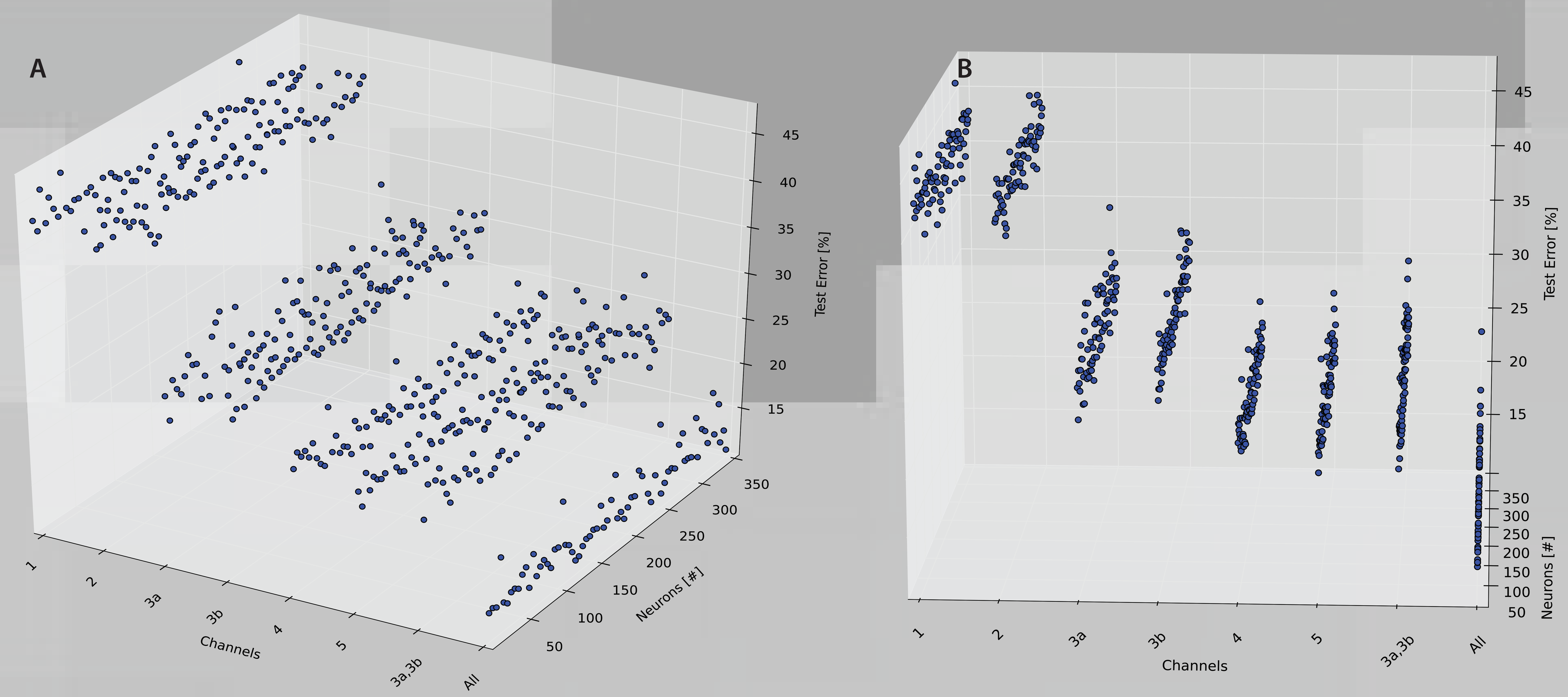

Fig. 4 - Two views of the same plot to summarize network performance. Error (false classification) displayed is only error on the test dataset, data the network was only exposed to once for testing to evaluate real-life expected output in which new situations are encountered. Channels 1 and 2 are clearly the least accurate, and the combination of 3a and 3b is more accurate than either alone. As expected the highest accuracy (73%-90%) is achieved by using all bands of the instrument.

Challenges/Future Work

Challenges

- Cloud/Smoke covering fire footprint
- Sun glint from bodies of water
- Data availability/timing of polar orbiter fly-overs
- Fire size and duration
- Surrounding surface temperature contrast
- Breaks in clouds triggering false positives
- Satellite navigation errors
- Vegetation cover (forest canopy)
- Satellite image resolution
- Determining real fire locations

Future Work

- Incorporate higher resolution data
- Utilize multiple satellite sources such as GOES
- Utilize radar imagery to include smoke plume detection
- Include fire risk parameters/forecasts to prioritize scan areas
- Compare accuracy of day/night and summer/winter cases
- Determine detection threshold for fire size
- Determine anthropogenic influence (parking lots, power plants)
- Time series prediction with neural networks
- Examine false classification cases for patterns/reasons for misclassification

Conclusions

For a network to be practical it must exhibit sufficient accuracy in detection and also present a reasonable demand on the available computational resources.

Evaluation of Network Design

- Training/Validation/Test/Total Classification Error
- False Positives, False Negatives, True Positives, True Negatives
- Amount of input data required
- Number of hidden layer neurons
- Number of training epochs

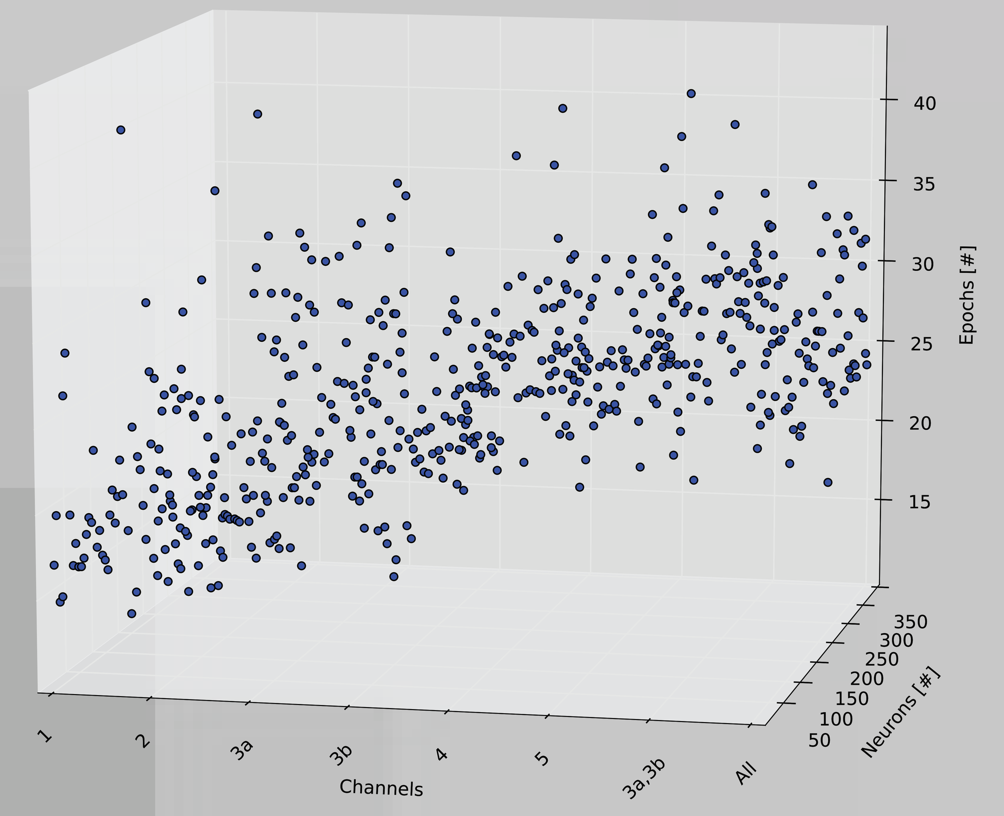

Fig.4 - The number of training epochs as a function of input channels and number of hidden layer neurons exhibits little dependence on the number of hidden layer neurons. There is a general increasing trend as more complex data is utilized, but the computational demands are within reason.

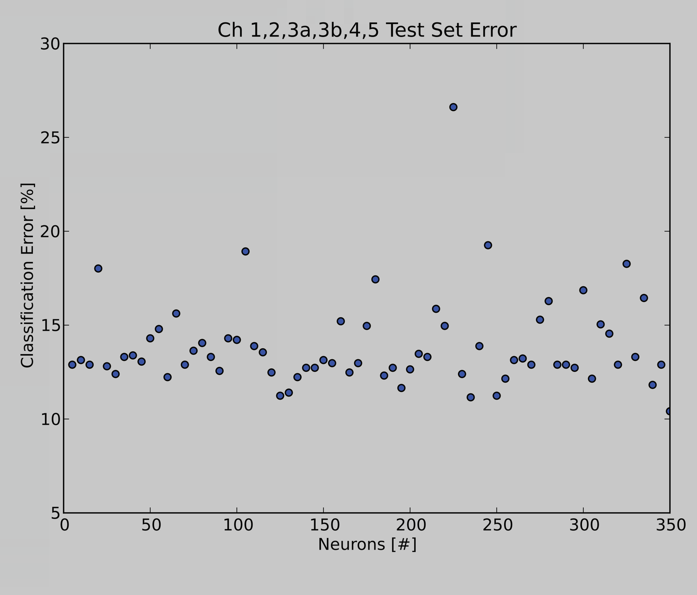

Fig.5 - Test set error when utilizing all bands of data from the AVHRR shows little improvement with increasing hidden layer neurons. There seem to be two weak minima around 125 and 240 neurons. The fewer neurons are desirable to reduce computation time.

Results Summary

The most accurate fire classification network used all 6 bands of AVHRR data to achieve an accuracy ranging from 73-90%. This variability is due to the random training of the network and random division of data into training, test, and validation data subsets.

Based on these results, neural networks have a place in a future suite of remote fire detection tools. Even with an accurate network, some human oversight is necessary to ensure quality detections. Future work such as implementation of more data sources could reduce network classification error.

Comparison of the 73-90% network accuracy with current algorithms is not possible as this network accuracy was determined with a limited number of cases. Scanning multiple satellite images with neural network and algorithmic methods, and then comparing the results would yield a better comparison. A combination of neural networks and algorithms is likely the most effective operational combination.

Most Effective Network Design

Number of Hidden Layer Neurons: *~125*
Input Vector Components: *600*
AVHRR Channels: *1,2,3a,3b,4,5*
Training Algorithm: *Scaled Conjugate Gradient*