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Firenet: Pursuing a Realtime Map of Active Fires Through Remote Sensing

4.5.24

**Executive Summary**

This project explored operationalizing a deep learning model that detects fires through satellite imagery. The purpose of the model is to generate a real-time map of active fires in the US. It operates by combining geostationary satellite imagery and Forest Service Landfire map layers as input with historical fire observations as training data labels. A google cloud platform pipeline was created to run the model for fire classification, but this work revealed significant issues with the initial model training producing a high number of false positive fire classifications. Future directions for this project will focus on retraining the model by redesigning the way the model is exposed to training data labels.

**Introduction**

The climate of the Earth in the last century is marked by a rising frequency of extreme weather events. While long-term prevention strategies are needed to address climate change, the immediate and unpredictable nature of these extremes necessitates short-term, reactive measures. Consequently, there is a pressing need to enhance quick decision-making processes in the emergency response to any climate-related disaster.

In recent times, the frequency and intensity of *large* wildfires in particular have increased[[1]](#footnote-1), making up the bulk of the total area burned each year. Responding to these fast-moving and devastating fires demands accurate data regarding the location of the fire's edge, its speed, and its likely path of spread. Gathering this crucial information poses significant logistical challenges and risks, as current methods to obtain data on the fire's status involve either aerial surveys or missions on the ground. This results in a critical shortage of near-real-time data on wildfire boundaries, increasing the difficulty of predicting fire behavior and adding to the hazardous nature of managing wildfires.

Satellite remote sensing offers opportunities to collect intelligence on fire behavior, yet it falls short in providing the necessary spatial or temporal resolution for precise and timely classifications of wildfire boundaries. Geostationary satellites like the Geostationary Operational Environmental Satellite (GOES) offer high-frequency observations of the Earth (every 5 minutes) but suffer from limited spatial resolution due to their great distance from the Earth's surface. Conversely, low Earth orbit (LEO) satellites, such as the carriers of the Visible Infrared Imaging Radiometer Suite (VIIRS) or Moderate Resolution Imaging Spectroradiometer (MODIS), deliver high spatial resolution but cannot provide continuous coverage because they orbit the Earth causing their coverage to have large gaps in time, around 12 hours, for any given location.

An article titled “A Deep Learning Approach to Downscale Geostationary Satellite Imagery for Decision Support in High Impact Wildfires” published to the journal *Forests* in 2021 laid the foundation for a deep learning model that could combine the temporal coverage of GOES with the spatial resolution of VIIRS[[2]](#footnote-2). Authors of this paper had developed a prototype model that would use the high-resolution, accurate fire classifications from VIIRS fires as training data, with GOES data as input.

For a little background on how computer vision neural networks work, there are two inputs needed. The independent variable is raw unstructured imagery. With facial recognition for example this might be headshots of people. The dependent variable is a set of labels associating a name with each individual face in the training data. Once the model trains on enough pairs of labels and raw imagery for any given individual, it can start to put names to faces on its own.

In the Firenet model, the VIIRS fire classifications would be the dependent variable, and GOES imagery would be the independent variable (along with a few others that will be discussed later.) The model starts to learn what fires look like in GOES imagery by having observed fire pixels overlayed on the imagery, similar to the face-labels. These labeled pixels come from the LEO VIIRS satellite. After the model sees enough instances of labeled GOES data, it starts learning to recognize what fires look like without assistance. The resulting model classifications could potentially be as accurate as VIIRS and as timely as GOES. Figure 1 is a diagram displaying the inputs and outputs of the neural network.

A diagram of a fire-hazard network

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**Figure 1:** Orange boxes are model input, green box is training data labels, and red boxes are output.

A colleague of mine spent time working on a grant to recreate this model and his code formed the basis for my capstone. The bulk of my capstone work involved refactoring his code to make it more modular, streamlined, maintainable, and automated. My other task was to deploy it to the cloud so that some of the long-running processes and scheduled prediction outputs could be displayed automatically and consistently. I accomplished these two tasks, streamlining the process of model retraining, which will be the future direction necessary for Firenet to move in before it can produce real value. A fully optimized Firenet could be useful for tracking large, fast-growing fires. It could trace their boundaries, calculate their speed of movement, and potentially even predict their path of spread.

**Neural Network Data Sources**

The data used in this project comes from three sources, these were introduced above but I will describe each in detail here. GOES imagery from the Advanced Baseline Imager Level 2 Cloud and Moisture Imagery (MCMIPC) product is the primary input. This is weather satellite imagery, and it is composed of 16 spectral bands. These bands correspond to light wavelength ranges visible and invisible. The most useful ones for fire detection are the infrared bands, especially band 7 shown below in figure 2. A map of the united states

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**Figure 2:** This is an image of the 7th band of the MCMIPC product from GOES-16 which captures the continental US. Band 7 with its short wavelength detection is highly sensitive to the temperature of a pixel[[3]](#footnote-3). A few fires are just barely visible as white flecks in Western Canada. This is a scan from August 17, 2023.

The resolution of GOES imagery is 2km per pixel, in other words each pixel represents a square 2 km wide and 2 km long[[4]](#footnote-4). This is very low resolution which is what makes using this imagery for fire detection challenging. To help alleviate this, Firenet uses a median composite of the last hour’s worth of imagery – 12 separate images, one every 5 minutes – as an input. This has the benefit of reducing false positive fire classifications, as sunlight reflectance may produce incorrect classifications in single scans but is unlikely to have a consistent signature over the course of an hour. This median composite of the continental US across 16 bands of imagery is the first data source for the model input.

The second data source is a set of map layers that are updated yearly and contribute information to the model about a given area’s potential to burn. These map layers are produced by Landfire a shared program between the U.S. Department of Agriculture Forest Service and the U.S. Department of the Interior[[5]](#footnote-5). The map layers are produced by a combination of field surveys and remote sensing. Landfire map layers used in the Firenet neural network input are the following:

* DEM layer: This layer represents a Digital Elevation Model (DEM). Elevation is crucial for understanding the topography of an area, which can influence the distribution and behavior of vegetation and fires.
* CBD layer: This layer indicates Canopy Bulk Density (CBD), which is a measure of the mass of an area's vegetation per unit area. It is used to assess the potential for biomass accumulation in the canopy, which can affect the behavior of fires.
* EVC layer: This layer shows Existing Vegetation Cover (EVC), which is a measure of the percentage of the landscape that is covered by vegetation. It is an important factor in assessing the fuel load that can contribute to wildfires.
* EVH layer: This layer represents Existing Vegetation Height (EVH), which is the average height of vegetation in a pixel. It is used to estimate the potential fuel load and can influence fire behavior.
* FBFM40 layer: This layer represents a standardized method for predicting fire behavior. It uses various fuel characteristics to estimate the burn potential of a given pixel.
* FVH layer: This layer represents Fuel Vegetation Height (FVH), which is a measure of the height of vegetation that serves as fuel for fires. This information is critical for predicting and managing the behavior of wildfires. [[6]](#footnote-6)

A map of the united states

Description automatically generated

**Figure 3:** This image shows the fuel vegetation height map layer for 2022, each pixel has a vegetation height associated with it.[[7]](#footnote-7)

The final data source is fire classifications from VIIRS. VIIRS is a LEO satellite that captures infrared data and uses a decision tree to classify active fires[[8]](#footnote-8). These fire classifications can be downloaded as tabular data where each row is a fire pixel and the columns are confidence level[[9]](#footnote-9), latitude, longitude and time. VIIRS training data preprocessing function seeks clusters of these points that are near each other in both space and time to use as inputs, these clusters represent fires. An example row of data is shown below in table 1.

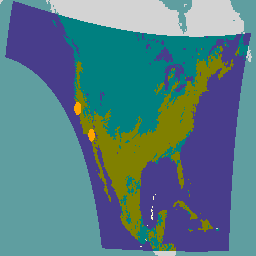
|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Latitude | Longitude | Acq\_date | Acq\_time | Confidence |
| 36.354759 | 76.804565 | 1/1/20 | 724 | high |

**Table 1:** Example row of VIIRS data, columns not used in training data are removed.

**Model Evaluation Data Sources**

The Firenet project’s map[[10]](#footnote-10) includes the fire classifications from the VIIRS satellite as described above. These classifications are the most important data source for model evaluation, because they are the labels that the model is trained to recognize. However, using VIIRS alone for comparison would be a mistake. This is because VIIRS does not have perfect temporal coverage, and fires that stop and start while VIIRS satellites are orbiting a different region of the earth will be missed by it entirely. As such, a well-trained Firenet would classify some fires correctly that according to VIIRS would be false positives. For this reason, a fire classification map with higher temporal coverage would be helpful to also include for comparison. Fortunately, in addition to publishing raw imagery, the GOES satellite also publishes a suite of processed imagery, including fire classifications.

The GOES satellite fire classification product is referred to as the Fire Detection and Characterization Continental United States (FDCC) product. An example visualization of this classification map is displayed in figure 4.



**Figure 4:** This is an example image from the FDCC imagery product. Each pixel is categorized according to a series of variables including the estimated temperature, and a variety of error measurements related to cloud conditions, sunlight reflection angle relative to the satellite etc.

The GOES FDCC product uses a decision tree with imagery bands 2, 7, 14, and 15 as inputs. The accuracy of this product itself is hard to measure as there are no apples-to-apples comparison datasets that match its temporal coverage[[11]](#footnote-11). Despite this, because it is the only product that could potentially match the temporal coverage of Firenet, it is a good auxiliary model evaluation dataset for Firenet. If Firenet can successfully combine the spatial resolution of VIIRS with the temporal coverage of GOES, it should match the fire boundaries of VIIRS and it should bear at least some correspondence with the classifications of FDCC in areas where VIIRS was orbiting a different region at time of classification.

The final fire classification source that is included in the display map for comparison purposes is MODIS. The classifications from MODIS are very similar to VIIRS. They come from a decision tree operating on infrared bands from a pair of LEO satellites, and are distributed from the NASA API as CSV data[[12]](#footnote-12). MODIS provides a second higher-resolution comparison source, and could potentially highlight any systematic flaws in using VIIRS alone as training data labels. Adding these MODIS classification boundaries was a relatively easy step as the functions for uploading VIIRS classifications could be reused with a few tweaks.

**Classification pipeline**

In this section of this document, the coding work[[13]](#footnote-13) that went into the data pipeline for this project will be explained piece by piece. I will describe these starting with the frontend display and moving towards the backend classification generation.

**Flask Server for Map Display**

Flask is a popular Python web framework that allows developers to create web applications quickly and easily while still having more control than they would using a framework like Streamlit. I created a Flask server to serve as the backend for my display map. On the frontend, I utilized Leaflet, an open-source JavaScript library for interactive maps. GeoJSON, a format for encoding geographic data structures using JSON (JavaScript Object Notation), is used to represent the map features. By combining Flask and Leaflet, I built a web application that displays a map capable of rendering GeoJSON strings as points and polygons. The GeoJSON format allows for efficient storage and transfer of geographic data between the server and the client. The map provides users with the ability to pan, zoom, and filter which layers they wish to view.

When designing the front-end display of fire classifications, it was necessary to choose between displaying fire classifications as TIFs vs. GeoJSON. TIFs are image files that can be mapped to a coordinate reference system (CRS) and GeoJSON as described earlier is a way of describing points, lines, and shapes on a CRS. The benefit of choosing to display TIF images would have been the capacity for a more fine-grained representation of model output. Each pixel’s shading might have added an extra dimension of model confidence. GeoJSON display is far more simplistic. For fire representation, it means model output will be simple points or polygons, indicating presence or absence of fire. Figures 5 and 6 show a comparison of TIF vs. GeoJSON format.

A map of the united states

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**Figure 6:** A fire probability TIF would look like this, where each pixel has a value between 1 and 100 for probability of an active fire.

**Figure 5:** This is an image from this project’s flask server, displaying GeoJSON points and polygons representing active fires.

One downside to the TIF option would be computational and storage costs. Each TIF encompassing the continental US would be roughly 100 MB large, which means storage costs would quickly skyrocket as a database of past fire predictions grows. A server constantly serving TIFS to multiple users would also get expensive (or slow) quickly. For reference the database at the time of writing contains 12,000 separate predictions, in their current form as GeoJSON, these take up about 20 MB of disk space. If these 12,000 predictions were all TIFS it would take up around 1,200 GB of disk space. Cloud computing and storage costs are currently only a few dollars per month for this project, using TIFS would likely increase these costs by at least 10x. Figure 7 shows a breakdown of cloud computing costs per month while using GeoJSON.

A graph with orange squares and white squares

Description automatically generated

**Figure 7:** Cloud computing costs in a typical month, taken from the google cloud console, the storage costs bar specifically would be more than 10 times larger with TIFS, and would grow rapidly over time as the archive of historical fire classifications grew.

The other downside to the TIF option is that it puts more of the burden of interpretation on the viewer. A viewer examining a TIF of continuous values representing fire presence probabilities is probably doing a mental conversion into something like fire polygons anyway, they are trying to understand what is and isn’t fire. With these considerations in mind, GeoJSON seemed a good choice, especially given the lack of resources to fund this project currently. Future iterations of this project should store predictions as both TIFS and GeoJSON, especially because an archive of historical classification TIFs may offer value in a model that predicts paths of fire spread.

**Google BigQuery Database**

The second part of the pipeline is the Google BigQuery (GBQ) database. GBQ is a cloud relational database that can hold simple data like numbers and character strings in tables that relate to one another. This is an ideal format for storing the GeoJSON strings. My GBQ database includes four tables, one for the Firenet classifications, then one each for the model evaluation classifications, FDCC, MODIS, and VIIRS. Each table is structured similarly with columns for GeoJSON strings and columns for the time the classification was made. Table 2 shows an example row of data.

A screenshot of a computer

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**Table 2:** The GeoJSON column in each table contains a series of GeoJSON ‘features’ which have a type and a set of latitude and longitude coordinates. The types in my database are all either “point” or “polygon.” The features together describe the active fires classified by a given product at a given point in time.

**Classification Functions**

The final overarching step in the classification pipeline is the ingestion of the most recent satellite data and the output of GeoJSON strings into the GBQ database. This step is the most complicated and involves several sub-steps. Figure 8 is a diagram for this step, breaking it down into four separate pipelines which terminate at the GBQ database. The function of each of these four pipelines is to ingest a satellite product data, perform various transformations, and output GeoJSON strings to GBQ.

A diagram of a cloud function

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**Figure 8:** Orange boxes represent cloud data sources and blue circles represent cloud compute instances.

The simplest of these four pipelines is the VIIRS comparison data. VIIRS data is downloaded from a nasa.gov API[[14]](#footnote-14), in the form of csv files. The classification pipeline downloads the most recent set of fire classifications every hour and converts them from a CSV to a GeoDataFrame (GDF). A GDF is a data structure provided by the GeoPandas library in Python, designed specifically for geographic data. Each row in a GeoDataFrame represents a geometric object (point, line, or polygon) with associated attributes. The key component of a GeoDataFrame that differentiates it from a regular DataFrame is the presence of a 'geometry' column that contains these geometric objects, which can be created from latitude and longitude values in the downloaded VIIRS CSV.

Once the VIIRS points have been converted to GDF format, they are clustered using the python library DBSCAN. DBSCAN looks for any geometries in the GDF that are 0.01 degrees[[15]](#footnote-15) away from one another, adding another column to the GDF indicating cluster number. The clusters are then filtered to only include instances where there are 5 or more points, and where at least one of those points is labeled high confidence by the VIIRS decision tree. Once these high confidence clusters are identified, a ‘convex hull’ polygon is drawn around each cluster.

A black and green arrows

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**Figure 9:** A convex hull is the smallest convex polygon that can enclose a set of points.

Each of these polygons is uploaded as a GeoJSON string, along with its timestamp to the GBQ database.

The second pipeline, for MODIS classifications operates in virtually the same way. The only difference is that confidence levels for MODIS classifications are represented as numbers between 0 and 100, with the threshold for display currently placed at 50 or higher. This pipeline is operated as a separate cloud function with mostly the same code as the VIIRS function.

The third of the four classification pipelines is the GOES FDCC pipeline. This pipeline operates on NetCDF (NC) files downloaded from the GOES google cloud bucket (this bucket is essentially a file folder in the cloud). Every part of working with this file-type, from downloading, to unpacking their nested structure, to reprojecting them to a CRS that could be converted to GeoJSON was difficult. A major bottleneck in this project for me was the steep learning curve in working with NC files.

NC datasets are designed to store and distribute scientific data. They are widely used in various scientific disciplines, especially in atmospheric and oceanic research. A NC dataset is a “dictionary of dictionaries” to use Python terminology, structured around several key components[[16]](#footnote-16):

* Dimensions: These define the shape of the data. For example, a global temperature dataset might have dimensions for latitude, longitude, and time. Dimensions are used to specify the size of variables.
* Variables: These contain the actual data stored in the dataset, such as light radiance values for satellite imagery. Each variable is associated with a set of dimensions that define its shape. Variables can represent scalar values (associated with zero dimensions) or arrays (associated with one or more dimensions). In the datasets I worked with, most variables were 2D arrays representing pixels in an imagery band. Each band was associated with a light wavelength range.
* Attributes: These provide metadata about the dataset, such as the units of measurement, data sources, or any other relevant information about the data or the dataset itself. Attributes can be global (applying to the entire dataset) or specific to individual variables.

NetCDF datasets are self-describing, meaning that they include information about the data they contain. This feature makes NetCDF files portable and easy to share between users and systems without losing the context of the data. NetCDF supports efficient access to large datasets with support for data compression and ‘chunking’ for optimized access patterns. All of these features are valuable, but a few subtleties of how these files work added complexity when attempting to make them interoperable with simpler Landfire TIF files[[17]](#footnote-17).

For the GOES FDCC NC files, the variable of interest was the data quality flag (DQF) variable. In the DQF array, points equal to 0 are high confidence fire pixels. Transforming this NC array into GeoJSON necessitates moving from the fixed projection of a GOES satellite to the EPSG 4326 CRS which maps to latitude and longitude. Figures 10 and 11 demonstrate the difference between a fixed projection and a typical CRS.

A grid of squares in a grid

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**Figure 10:** This figure demonstrates how a fixed grid projection system works in a simplified way. Note that grid squares along the edges represent more land-cover than grid squares in the middle.

A map of the world with red dots

Description automatically generated

**Figure 11:** A typical CRS maps a grid to a flattened model of the Earth’s surface.

There is a complicated trigonometry equation that can be used to transform grid square indices from the coordinate reference system to latitudes and longitudes, and there are also GIS python libraries that can handle reprojection. I ended up using a third approach that seemed to work more consistently with NC files, using a reference file which simply mapped each fixed projection grid square index to a latitude and longitude center point. This is effectively a ‘lookup table’ provided to accompany GOES data. Using a python function with this lookup table to locate the latitude and longitude of each array index where DQF equals 0 allowed me to convert fire locations into a GDF, and then to GeoJSON which is uploaded to GBQ as in the last pipeline.

The fourth and final pipeline integrates multiple satellite data sources, matches them to a common CRS and resolution, and runs the neural network before generating GeoJSON classification polygons. This pipeline is the most complex by far, but it draws on many of the concepts explained in the previous two pipelines. To start with I will display a diagram of this pipeline in figure 12.

A diagram of a private bucket holding

Description automatically generated

**Figure 12:** This pipeline is composed of three functions, the Landfire uploading function runs once a year – whenever Landfire layers are updated. The median composite function runs every 5 minutes – each time the GOES satellite scans the continental US. The containerized Firenet function currently runs every 12 hours to keep costs down, but it could run every 5 minutes with more funding.

This Landfire function accesses the Landfire TIFs which are natively 30 meters per pixel and resamples them to match the resolution of the training data labels – 375 meters per pixel. Resampling is the process of changing the resolution of an image file to a desired resolution. In this case, Landfire is being down-sampled, the resolution is decreased to match the training data resolution. This process loses a lot of information, effectively turning the Landfire layers into ‘pixelated’ versions of themselves, but it is a necessary step to match all input resolutions with each other before feeding them into the neural network. Rioxarray is a python package that has methods to change the CRS and resolution of satellite imagery, and this compositing function and the Firenet function rely on this package.

In the Landfire function, the resampled reprojected Landfire layers are also cropped to a particular bounding box in the Western US. The reason for cutting down the layers this way is that it reduces the computing costs to run Firenet. By working with a small but important region to process fire classification for, the project can demonstrate the capacity of Firenet without costing too much. After being clipped to a bounding box, the Landfire layers are stacked in an NC file, and uploaded to the private cloud bucket. They serve as a template that has been matched to the correct resolution, CRS, and spatial extent. Changing this Landfire reference NC file in the private bucket can redirect the ‘attention’ of Firenet to a different region, which will be as easy as changing the coordinates in the bounding box argument of the LANDFIRE function.

The median composite function downloads the 12 most recent MCMIPC NC files and finds the median value of each band at each pixel to reduce noise in the input. This function then downloads the Landfire NC, matches the MCMIPC files to its resolution, CRS, and extent, and stacks them into a single NC file. A feature engineering function then creates four new imagery bands by calculating ratios of values in existing bands.

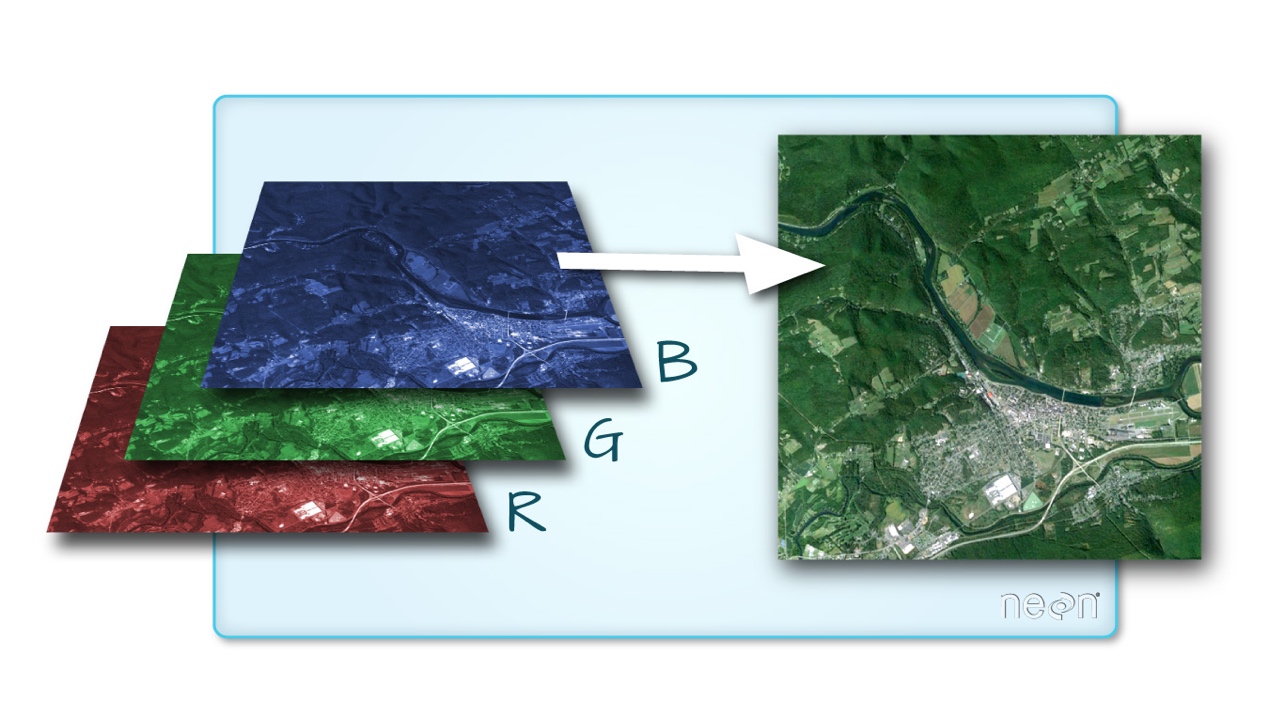
This "band arithmetic" feature engineering technique is common in satellite imagery analysis. The principle of this technique is that certain objects on the ground can be best highlighted by comparing the values in one spectral band to another. It's like using specific filter combinations in photography or image editing software to bring out certain details or colors in a picture. Just as a red filter emphasizes reds while a blue filter emphasizes blues, calculating ratios between different spectral bands can enhance the visibility of fires, vegetation, or other ground features of interest by exploiting their unique spectral signatures across multiple bands. Band arithmetic acts as a set of customized "spectral filters" to make the desired objects pop out from the background noise in the satellite imagery.

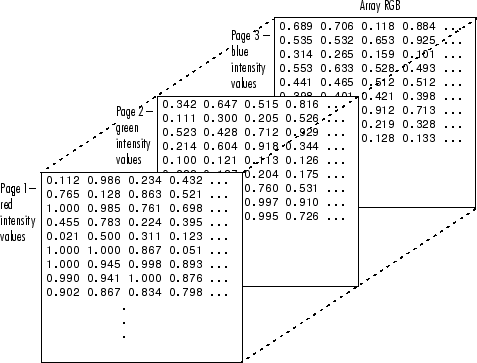
For instance, the Ratio Vegetation Index[[18]](#footnote-18) in remote sensing is calculated by dividing the near infrared band by the red band, which highlights healthy vegetation, because healthy vegetation reflects more infrared than red light. The Firenet model creates a set of engineered bands similar to this, taken from the specifications in the *Forests* article mentioned in the introduction that proposed the model.

* Channels 6/5: Enhances contrast between fire-affected areas and snow/ice or clouds, aiding in the neural network's ability to distinguish fires from other bright surfaces.
* Channels 7/5: Improves the neural network's capability to detect fires under varying lighting conditions by leveraging differences in reflectance between fire and non-fire surfaces.
* Channels 7/6: Assists the neural network in differentiating between fire and cloud particles by exploiting the distinct thermal properties and sizes of cloud and fire particles.
* Channels 7/14: Enhances the neural network's ability to identify fires by comparing longwave infrared emissions with shortwave emissions to detect heat sources.

After feature engineering, all unused bands are removed from the dataset, leaving a 21-band image, which is uploaded to my private cloud bucket. This image contains within it all the information necessary for Firenet to identify fire boundaries, at least in theory.

The final step in the pipeline is the function that runs Firenet. This function downloads the output from the previous function as input, and outputs the fire boundary classifications as GeoJSON. After downloading the previously described 21 band raster image as input, this function needs to transform the raster imagery bands into a three-dimensional array of normalized numbers.

The best way to conceptualize this three-dimensional array is by understanding its components, which are two-dimensional arrays of numbers that correspond to different imagery bands. Figure 13 shows a simplified version of this. 



**Figure 13:** Each imagery band can be represented as a two-dimensional array of numbers between 0 and 1, indicating the value at each pixel for the band in question. The neural network input includes 21 bands instead of three, including invisible light, engineered features, and Landfire layers with vegetation height, density, etc.

Once the data has been turned into this 3-D array, it is almost ready to be classified by the neural network. Two things need to happen before this can occur though. First, the array needs to be broken into small chunks. The model input begins as a 1748x2266x21 array representing the subsection of the Western US discussed above, and is converted into 945 21x64x64 chunks. Each of these chunks represents an area of roughly 140,000 acres. Chunking in this way allows the neural network to recognize fires more easily since they are taking up a larger proportion of the chunk.

This process is like taking the landscape image as a whole and splitting it up into puzzle pieces. The model can better identify fires one puzzle piece at a time, rather than process the entire landscape. A vital step at this stage is to find a way to save georeferencing metadata associated with each chunk. In the puzzle analogy, this is like creating a puzzle map, where each piece is labeled with its position in the landscape. The neural network works with arrays of raw numbers, so this map has to be saved as a separate object.

To save this metadata, I used the approach of creating a ‘template’ raster grid. I took the original 21 band raster, deleted 20 of the bands, and overwrote the remaining band with null values. This is essentially an emptied-out map where every grid square corresponds to a real location, but the value associated with that location is a null. These empty grid squares will eventually be filled with a probability of fire at each location.

While chunking up the data, each chunk is assigned an index number in a list. These chunk index numbers are the puzzle piece labels that gives a later function information on how to stitch outputs back together. Each time the neural network created a classification output from the chunk input, I associated the appropriate puzzle piece label with the output. Once all outputs were created I used these labels to ‘mosaic’ all the small chunks into the original 1748x2266 shape. Lastly, I overwrote the null raster grid values with the values in this array.

At this stage there is a raster file mapped to the region of interest in the Western US. Each pixel has a value between 0 and 1 that indicates fire-probability. With this as input, I used an approach very similar to what was previously described for clustering and thresholding the VIIRS cross-evaluation data. I create a cutoff point at 0.95[[19]](#footnote-19), and then look for clusters of 5 or more pixels close to each other that have values higher than that cutoff. After these clusters are located, convex hull polygons are drawn around each, converted into GeoJSON, and uploaded to Google BigQuery.

**Model Accuracy Assessment**

To give away the conclusion of this section, our model predictions in their current form do not correspond well to reality, but there are a few clear opportunities to improve its performance. This model was created using a standard practice of splitting the source data into sets of “training” and “testing” data. The model is developed using the “training” data, and its effectiveness is evaluated on the “testing” data that it has never “seen.” This involved keeping a set of the VIIRS training labels reserved, only training with 80% of the available labels. The model then attempted to classify fire boundaries on the other 20% of inputs we had labels for. This standard practice is used to monitor for “overfitting,” which is where a model learns the patterns of its training data in a way that can’t be extrapolated to previously unseen data. The testing indicated a dice coefficient of 0.21.

A dice coefficient can range from 0 to 1 where 0 indicates no overlap between predictions and reality and 1 indicates perfect overlap. It is a good metric for model evaluation because it considers both false positives and false negatives. A dice coefficient of 0.21 generally would indicate a poorly performing model, but we thought our model might be usable with some tweaking. This was especially true considering that no other products could classify fires with such temporal frequency, so even a moderately accurate product was better than what is available. Viewing model outputs during the initial model training process, there were many instances of promising correspondences between model predictions and training data. Figure 14 shows two of these correspondences, with model predictions on the left and validation data on the right.

A blue and green image

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Description automatically generated

A green and yellow square

Description automatically generatedA purple and green background

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**Figure 14:** These and other examples of correspondence seemed promising enough to move forward with the model. The axes are pixel counts in chunks.

At the time of initial model evaluation, it was quite reasonable to expect that through tuning model parameters and inputs, and increasing the size of the training data, a useful model could be created eventually. Once I created the full model-classification pipeline which allowed georeferencing of predictions on the entire continental US however, a more significant hurdle to creating a model with real-world value came to light.

What I found is that the model is seeing a *lot* more fires than it should, even considering the low dice score. We think that this was not obvious during the initial training and evaluation because both the training and test data always included a fire somewhere at the center of each image, so there wasn’t much opportunity to catch the model ‘hallucinating’ fires that didn’t exist at all.

In hindsight, this was a major mistake in model training. What seems to have happened is that the model learned the most consistent pattern in its training data, which was that somewhere near the center of each input chunk there is a fire. This glaring issue was not obvious until we started giving it large areas without fires to evaluate, and we realized it was seeing fires in the middle of every input chunk. The model now needs to be retrained, which I will explain next. Fortunately, the work that went into my capstone of creating these pipelines that made the various satellite imagery products interoperable will streamline the retraining process significantly.

**Model Retraining**

Where the previous training attempt created small raster chips surrounding fires, an effective training function will instead create larger rasters that cover the entire field of view of the VIIRS satellite at any given point in its orbit. Most of the raster area will be entirely absent of fires. These large rasters can be stacked with the input from the previously engineered pipelines and chunked into 64x64 chunks, many of which will include no fires. Figure 15 shows how training data chunks will be created for model retraining.

A grid with a map

Description automatically generated

**Figure 15**: The orange polygon represents a fire label. With grid squares representing model input chunks, we will have many cases of chunks without fires for the model to learn from. Additionally, the chunks that include fire presence will not all have fires positioned in the center.

Another benefit of creating the training chunks this way is that we can experiment with overlapping sets of chunks, which means the training data could be increased arbitrarily as we slice up the active fires in different ways. This would be akin to giving the neural network multiple exposures and perspectives on the same fire patterns from slightly varied vantage points. Much like how rotating an object lets you see it from all angles, taking overlapping chunk "snapshots" of the same fire areas provides the neural network with additional variation examples that reinforce its ability to generalize the salient fire patterns. Even without this technique of synthetically increasing the training data volume there are 2 additional years of overlap between VIIRS labels and GOES input that weren’t included in the initial training data.

Experimenting with the input bands also has significant potential for improving model accuracy. Many of the bands included in the original model primarily capture cloud cover or atmospheric phenomena, and these bands are likely just noise for a model trying to classify fires. Band 8 for instance, shown below in figure 16 is referred to as the upper-level water vapor band. It is primarily used for identifying jet streams and turbulence signatures. Removing bands like this one when retraining should produce a more accurate model.

A map of the united states

Description automatically generated

**Figure 16:** A band-8 scan is shown here from August 17 2023, large fires that are visible in other bands are completely invisible here.

Another area where experimentation may yield more accuracy is with the neural network’s hyperparameters. Hyperparameters are basically settings that can be tuned for how neural networks learn. Testing different hyperparameters is likely less important than being more selective about model input and fixing the issue with fires always being centered, but it may still have a significant effect on model accuracy. Some of the hyperparameters for initial model training are listed below with explanations and recommendations.

* **Number of Epochs** The number of epochs was set to 50. This parameter indicates how many times the training data is passed through the neural network while it is learning the data’s patterns. More epochs are essentially giving the model more chances to fine tune its pattern recognition, usually a point of diminishing returns is reached, but it likely will be a point higher than 50.
* **Learning rate:** The learning rate for initial model training was set to 0.002. A lower learning rate may be more effective for adapting to a complex “loss landscape,”[[20]](#footnote-20) especially with more epochs. The learning rate essentially adjusts how large the corrections the model makes to its mistakes with each epoch, more epochs with smaller corrections are good for a complex pattern recognition task. The low initial number of epochs and high learning rate choices were partly due to the time limitations of trying to train the model overnight on a laptop, which are not as relevant now that the project is being run in the cloud.
* **Optimizer:** The model optimizer used for training was the Adam optimizer, it determines how learning rates may be adapted per parameter across epochs. Testing other optimizers may yield better results.

Other model hyperparameters are a bit more complex like “kernel size” and “pooling size.” Through conversations with my collaborator who is experienced with using neural networks to detect land cover however, these are already likely to be near-optimal. These more complex ‘architectural’ hyperparameters are less frequently tuned when experimenting with an image segmentation neural network. Tuning the architectural hyperparameters like these is akin to changing the ingredients in a cake recipe while changing the more simple hyperparameters is more like changing the oven temperature and bake time. To carry this metaphor further, none of this process-changing will amount to much while our inputs are still the equivalent of rotten eggs.

**Conclusion**

The process of working on this project provided immense educational value, serving as an invaluable introduction to utilizing neural networks and the Google Cloud Platform infrastructure. It also allowed me to significantly develop my skills in working with and processing diverse satellite imagery data sources. While there is still considerable work to be done before this fire detection model can be considered truly viable, the potential impact it could have on assisting real-time tracking of large, rapidly spreading wildfires is immense. Even modest improvements in this area could be tremendously valuable.

The primary impact of this capstone project was identifying a critical flaw in the initial model training approach that likely caused the underwhelming accuracy results. By highlighting the need to provide the neural network with more realistic and representative training examples covering full satellite scenes, not just fire-centric clips, the path forward has become clear. The extensive data pipelines built out as part of this work create a streamlined foundation making it straightforward to implement this updated retraining methodology. With the infrastructure now in place, a retrained model utilizing the new training approach can easily replace the current underperforming version, allowing for further iterative accuracy evaluations and refinements.

Looking at the bigger picture, successfully resolving the challenge of accurately classifying active fire boundaries from GOES geostationary satellite imagery would represent a monumental achievement in the field of remote fire sensing and monitoring. The ability to provide a real-time fire mapping product with boundary updates every 5 minutes, rather than the 12-hour latency of current VIIRS products, could dramatically improve wildfire prediction, containment, and suppression efforts. Delivering such frequent high-fidelity active fire intelligence could save lives, reduce property damage, and mitigate environmental impact by enhancing the information positioning of firefighting resources.

While this capstone project has not yet realized that ultimate goal, it has illuminated the roadmap and established a strong technical foundation to continue pursing it. By addressing the deficiencies identified, optimizing training data composition, and iterating on model refinements, the promise of an operational real-time GOES-based fire detection and boundary mapping system remains achievable. Continued work in this vein holds important potential upsides for enhancing public safety and environmental conservation in the face of intensifying wildfire risk.

1. National Oceanic and Atmosphere Administration (NOAA) article titled ‘Wildfire Climate Connection’ can be found [here](https://www.noaa.gov/noaa-wildfire/wildfire-climate-connection). It contains links to several studies documenting wildfire increase. [↑](#footnote-ref-1)
2. Read the paper [here.](https://www.mdpi.com/1999-4907/12/3/294) [↑](#footnote-ref-2)
3. More info on band 7 [here](https://cimss.ssec.wisc.edu/goes/OCLOFactSheetPDFs/ABIQuickGuide_Band07.pdf). [↑](#footnote-ref-3)
4. Pixel resolutions differ depending on their position. Pixels near the edges of the field of view are ‘stretched’ as the curvature of the earth means more land cover for that grid square. GOES imagery is typically referred to as having 2km per pixel resolution for simplicity. [↑](#footnote-ref-4)
5. General information on Landfire [here.](https://www.landfire.gov/about.php) [↑](#footnote-ref-5)
6. Landfire layer specific information [here.](https://www.landfire.gov/documents/LF_Data_Product_Descriptions_w-References2019.pdf) [↑](#footnote-ref-6)
7. View an interactive Landfire map [here](https://www.landfire.gov/viewer/) to examine all the layers. [↑](#footnote-ref-7)
8. Find info on the VIIRS fire classification algorithm [here](https://viirsland.gsfc.nasa.gov/PDF/VIIRS_activefire_User_Guide.pdf), beginning on page 4. [↑](#footnote-ref-8)
9. VIIRS confidence levels are based on outputs from the fire classification decision tree, for more information see this [link](https://www.earthdata.nasa.gov/faq/firms-faq#:~:text=For%20VIIRS%2C%20the%20confidence%20values,of%20individual%20hotspot%2Ffire%20pixels.). [↑](#footnote-ref-9)
10. View map [here.](https://firenet-99.uw.r.appspot.com/) [↑](#footnote-ref-10)
11. For a discussion of the difficulty of measuring FDCC accuracy, see page 57 of the FDCC theoretical basis document [here](https://www.star.nesdis.noaa.gov/goesr/docs/ATBD/Fire.pdf). [↑](#footnote-ref-11)
12. See more info on MODIS [here](https://modis-fire.umd.edu/files/MODIS_C6_C6.1_Fire_User_Guide_1.0.pdf), and view the API [here](https://firms.modaps.eosdis.nasa.gov/api/country/). [↑](#footnote-ref-12)
13. Check out my project GitHub [here](https://github.com/hunterad93/firenet). [↑](#footnote-ref-13)
14. <https://firms.modaps.eosdis.nasa.gov/api/country/> [↑](#footnote-ref-14)
15. Degrees are a unit of angular measure, often used to describe coordinates on the Earth's surface in the form of latitude and longitude. One degree is defined as 1/360th of a full rotation around a circle. In the context of the Earth's surface, 0.01 degrees is roughly equivalent to 0.69 miles, although this conversion differs at different latitudes and longitudes. [↑](#footnote-ref-15)
16. NetCDF user’s guide can be viewed [here](https://docs.unidata.ucar.edu/nug/current/). [↑](#footnote-ref-16)
17. A particularly difficult stumbling block was discovering (after many hours) the hidden “encoding” attribute of rioxarray datasets, which was indicating conflicting CRS information for GOES imagery which caused errors when attempting to reproject it to match the CRS of Landfire imagery. [↑](#footnote-ref-17)
18. <https://en.wikipedia.org/wiki/Vegetation_index> [↑](#footnote-ref-18)
19. This chosen cutoff is a placeholder, after model-retraining a new threshold should be found through experimenting with what leads to the best convergence with comparison classifications. [↑](#footnote-ref-19)
20. In machine learning, the loss landscape refers to the high-dimensional surface formed by the loss function, which quantifies the difference between the model's predictions and the actual target values. The loss landscape is a visual representation of how the model's performance (measured by the loss function) changes as the model's parameters (weights and biases) are adjusted during training. A complex loss landscape is characterized by numerous local minima, steep gradients, and flat regions, making it challenging for the optimization algorithm to find the global minimum (i.e., the set of parameters that results in the lowest loss). [↑](#footnote-ref-20)