# Crop Yield Estimation of Rice Crop for India

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## Motivation

Crop yield forecasting plays a vital role in the pursuit of sustainable development. Predicting crop yields, such as wheat or rice, can help municipal governments plan out food sources and distribution for its population and can transform into an early indicator of famine. Deep learning approaches to forecast yield are both quicker and more inexpensive compared to traditional tools. This vast reduction in time and capital makes this approach scalable to many countries in various stages of development. It is a promising technique to promote sustainability and food security on a global scale.

## Data

1. **Satellite imagery consisting of 9 total bands**
   a. Multispectral satellite images at 500 meter resolution (bands 1 through 7)
   b. Land surface temperature (bands 8 and 9)
   c. Land cover mask that filters satellite data to contain only cropland
2. **Historical yield data from rice croplands**
   a. Year-State-District-Season-Yield
   b. Yield is quantified in tonnes per hectare

In total, we obtained 42,336 raw satellite images for the Indian region for the years 2003 to 2009

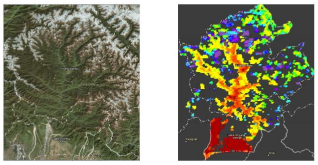
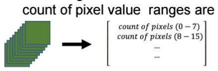


**Fig. 1: Dibang Valley in Arunachal Pradesh State**

## Features

**Data transformation - Dimensionality Reduction:**

- Key assumption of *permutation invariance:*
  - Location of pixels do not matter, count of pixels matter in predicting food yield
- Raw images for each of the 9 bands are converted to a histogram where the count of pixel value ranges are encoded within 32 bins.




9 bands images for 32 time steps of each location-year combination were transformed into a histogram matrix of shape 32 x 9

## Methodology and Models

**Models:** We trained multiple **CNN** and **LSTM** models

- Each X input: **32 bins** X **32 timesteps** X **9 bands**
- Each Y was **rice yield** for a district-year combination
- Evaluation metric: **Root Mean Squared Error**
- Additional metrics considered: **R-squared, Mean Abs % Error**
- Overall, trained shallow models given the sparsity of dataset

**CNN Model Architectures**

| Layer | Best Model | Simpler Model | Deeper Model |
|---|---|---|---|
| CONV(64,3,1) | 1 | 1 | 1 |
| MAXPOOL(2,1) | 0 | 1 | 1 |
| CONV(128,3,1) | 1 | 0 | 1 |
| MAXPOOL(2,1) | 1 | 0 | 1 |
| CONV(256,3,1) | 0 | 0 | 1 |
| FC(512) | 1 | 1 | 1 |

***Additional hyperparameter tuning:*** *best model did not include dropout, but included L2 regularization. Dropout was added for the deeper model.*

**LSTM Model Architectures**

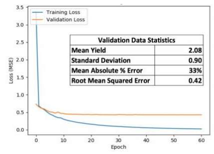
| Layer | Best Model | Deep 1 | Deep 2 |
|---|---|---|---|
| LSTM(32)* | 2 | 2 | 2 |
| LSTM(64)* | 0 | 1 | 2 |
| LSTM(64) | 0 | 1 | 0 |
| LSTM(32) | 1 | 0 | 1 |
| Dense(32) | 0 | 1 | 0 |
| Dense(10) | 1 | 0 | 1 |
| Dense(1) | 1 | 1 | 1 |

***Additional hyperparameter tuning:*** *best model had learning rate 0.001, batch size = 25, no dropout.*

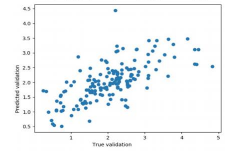
## Results

**CNN Model: We achieve an RMSE of 0.42 tons/hectare, and an MAPE of 33%.**

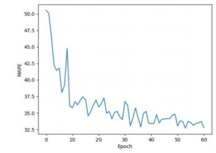
### Loss Curve




### Predicted vs Actual Plot

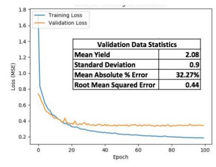



### Mean Absolute % Error

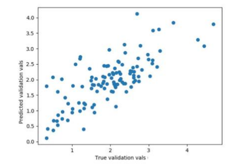



**LSTM Model: We achieve an RMSE of 0.44 tons/hectare, and an MAPE of 32%.**

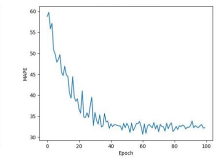
### Loss Curve




### Predicted vs Actual Plot



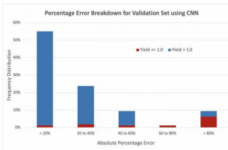

### Mean Absolute % Error

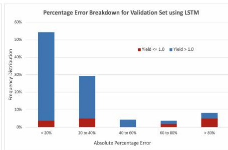



## Error Analysis

Principal error analysis steps:

- Cleaning up low-density data with yield values below 0.2
- Setting a bottom threshold for yield values skewing MAPE
- Analyzing performance on low vs. high yield values **(fig. on right)**




## Conclusion and Future Steps

- Crop yield data can be forecasted with relatively high accuracy using just remote-sensing data
- Shallow LSTM and CNN models did better than deeper models due to sparsity of data
- Next steps include deeper error analysis to understand features of poorly classified images
- Finally, we hope to perform similar forecasting for additional crops under different seasons