Crop Yield Estimation of Rice for India

Ifeoma Anyansi, Adeesh Goel, Agneya Loya
CS 230 (Deep Learning), Stanford University

(ianyansi,adeesh,agneya)@stanford.edu

Andrew Ng
Kian Katanforoosh

STANFORD UNIVERSITY

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 less expensive 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) collected at 8-day intervals
   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 tons per hectare

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

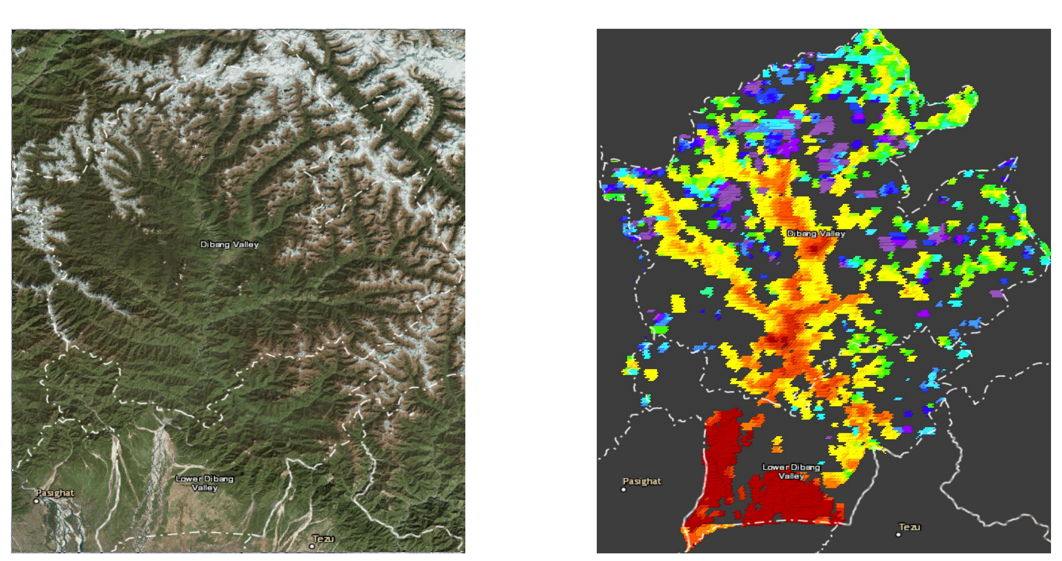
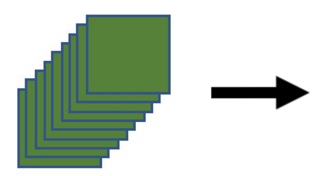


Fig. 1: Dibang Valley in Arunachal Pradesh State
left: satellite imagery right: temperature data

Features

Data transformation - Dimensionality Reduction:

- Key assumption of *permutation invariance:*
  - Location of pixels do not matter; count of pixels matter for yield prediction
- Raw images for each of the 9 bands were converted to a histogram where pixel value frequencies were encoded within 32 bins. Result: 1323 data points



$$\rightarrow \begin{bmatrix} \textit{count of pixels } (0-7) \\ \textit{count of pixels } (8-15) \\ \cdots \\ \cdots \end{bmatrix}$$

9 band images for each time step and location-year combination were transformed into a histogram array of shape 32 x 9 (i.e. # of bins x # of bands)

Model and Methodology

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

- Each X input: **32 bins** X **32 timesteps** X **9 bands**
- Each Y output: **Rice yield** for a district-year combination
- Evaluation metric: **Root Mean Squared Error**
- Additional metrics considered: R^2, **Mean Abs. Percentage Error**
- Overall, shallow models were trained given the scarcity 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 tuned: *Best model did not include dropout, but included L2 regularization. Dropout was added for the deeper model. Early stopping was used.*

LSTM Model Architectures

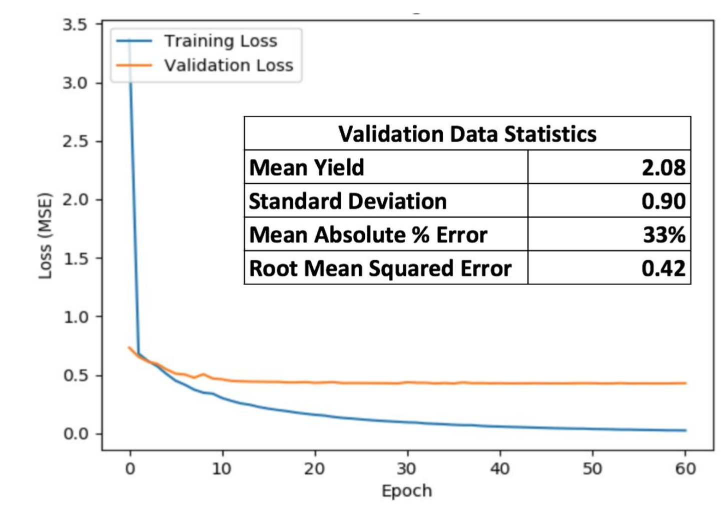
Layer	Best Model	Deep 1	Deep 2
LSTM(32)*	2	2	2
LSTM(64)*	0	1	2
LSTM(64)	0	1	0
LSTM(32)	1	0	1
Dense(32)	0	1	0
Dense(10)	1	0	1
Dense(1)	1	1	1

****Additional hyperparameter tuned:*** *Best model had learning rate 0.001, batch size = 25, no dropout. Early stopping was used.*

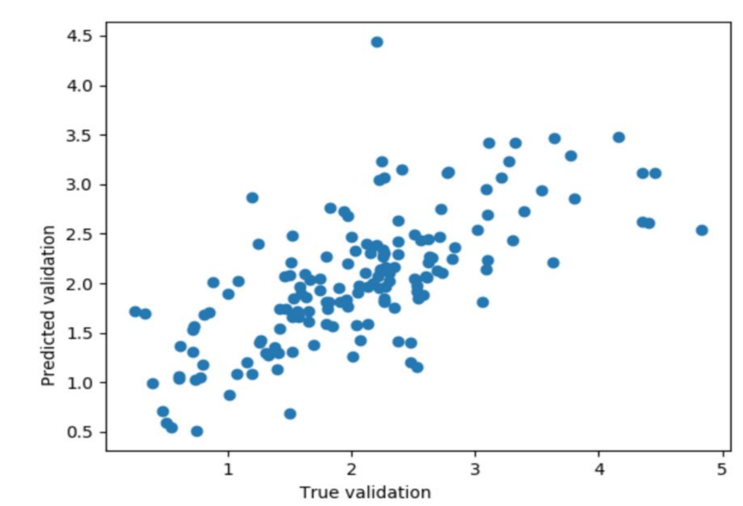
Results

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

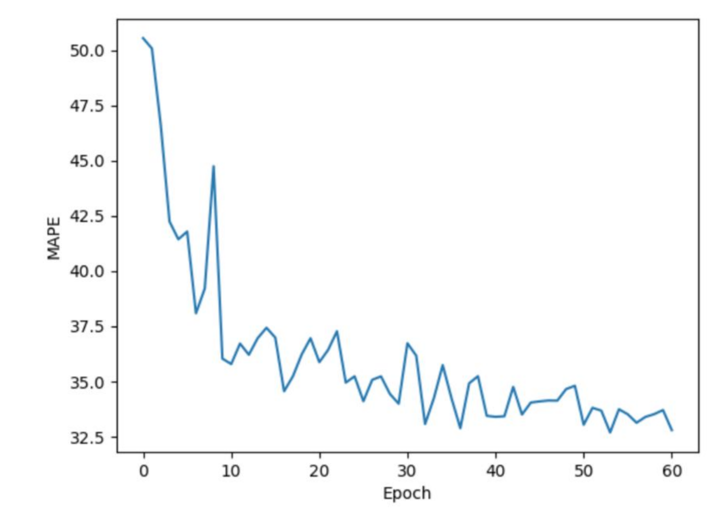
Loss Curve



Predicted vs Actual Yield

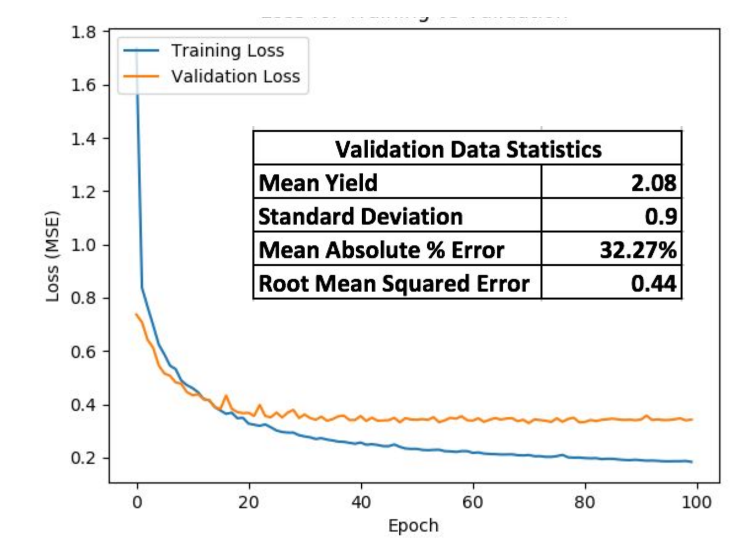


Mean Absolute % Error

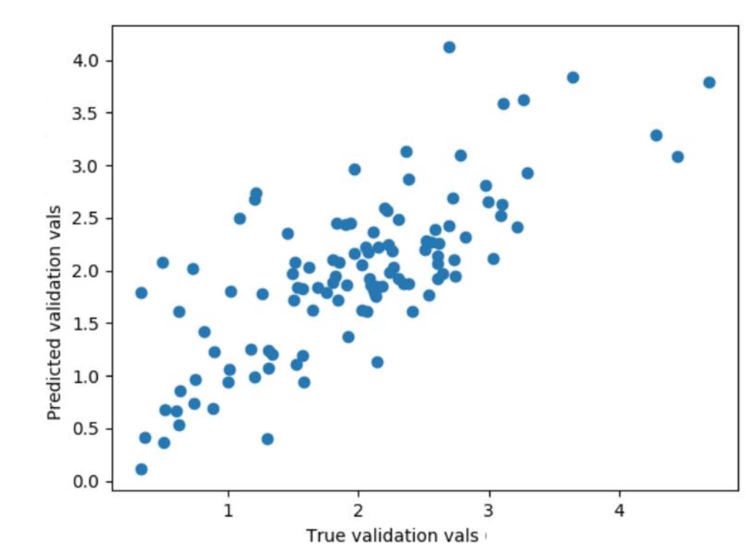


LSTM Model: We achieve an RMSE of 0.44 tons/hectare, and an MAPE of 32%.

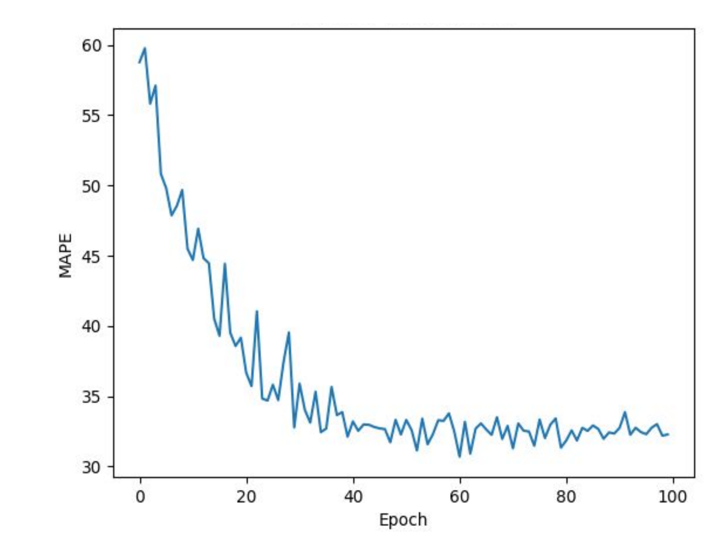
Loss Curve



Predicted vs Actual Yield



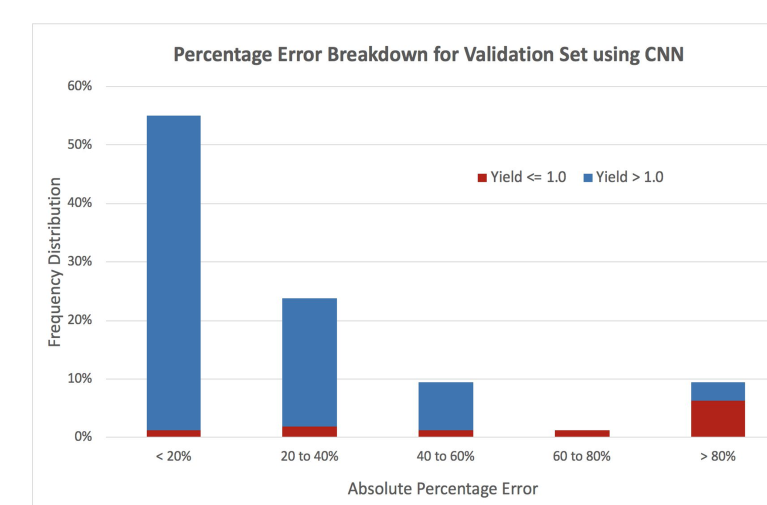
Mean Absolute % Error

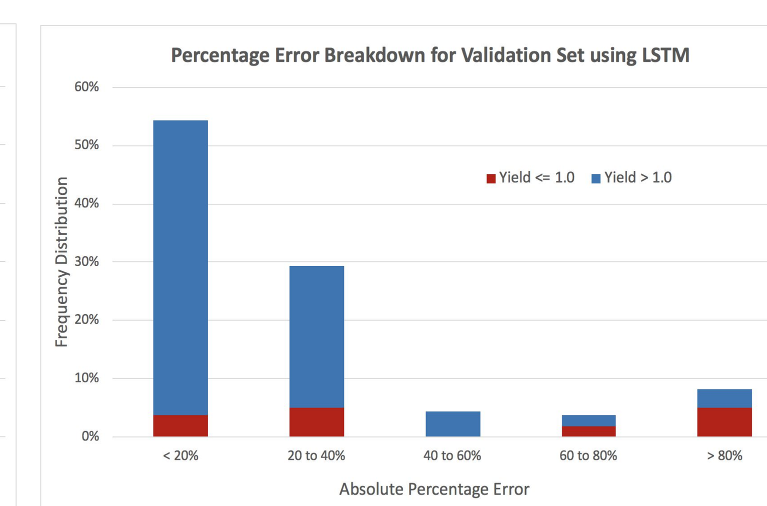


Error Analysis

Principal Steps:

- Removed low-density image data
- Set a bottom threshold for yield values skewing MAPE
- Analyzed 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 scarcity 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

References: You, Jiaxuan, et al. "Deep gaussian process for crop yield prediction based on remote sensing data." Association for the Advancement of Artificial Intelligence (2017).
Sabini, Mark, Rusak, Gill and Ross, Brad "Understanding Satellite-Imagery-Based Crop Yield Predictions." CS231N (2017)