AgriCast: A Novel Environmentally-Driven Framework for In-Season Crop Yield Forecasts via Machine Learning

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Climate change continues to disrupt agricultural systems, making crop yield forecasting a critical component towards enabling climate resilience in agriculture. This project aimed to decipher the impacts of various environmental factors on field crops, in order to develop deep learning-based crop yield forecasting frameworks using climate and soil attributes for early, interpretable, and accurate yield predictions months ahead of harvest. Here, 388 climate, soil, elevation, and yield attributes were collected from a ~100-year time span, forming one of the most comprehensive county-level environmental datasets compiled for yield forecasting. After preprocessing, Shapley Additive Explanation (SHAP) values were computed for each attribute, indicating extreme temperatures during later summer months (DX90, EMXT) as having outsized negative contributions towards soybean yields, while also identifying several novel drivers (DYXT, DYNT). A deep learning neural network was meticulously tuned using the significant factors, resulting in an accurate and robust end-of-year soybean yield prediction model. With monthly climate attributes, this framework, AgriCast, was then able to produce yield forecasts in May, June, July, and August, with an R^2 of 0.83, 0.838, 0.849, and 0.86, respectively, showing that AgriCast can accurately predict yields up to five months ahead of harvest. Furthermore, this framework was able to be applied to other crops, including corn, achieving similar metrics (R^2>0.88) for in-season forecasts, validating the framework's broader applicability. With implications towards long-term food security, AgriCast allows farmers and policymakers to reliably forecast future yields, enabling more informed decisions to support future sustainable agriculture.

Awards Won:

Third Award of $1,200