Towards Resilient Agriculture to Hostile Climate Change in the Sahel Region: A Case Study of Machine Learning-Based Weather Prediction in Senegal

Chimango Nyasulu [1] Awa Diattara [1] Assitan Traore [2] Abdoulaye Deme [3] Cheikh Ba [1]

[1]LANI (Laboratoire d'Analyse Numérique et Informatique), University of Gaston Berger, Saint-Louis, Senegal [2]Business & Decision, Grenoble, France
[3]Laboratoire des Sciences de l'Atmosphère et de l'Océan, Unité de Formation et de Recherche de Sciences Appliquées et de Technologie, University of Gaston Berger, Saint-Louis, Senegal

INTRODUCTION

- To ensure continued food security and economic development in Africa, it is very important to address and adapt to climate change [1].
- Excessive dependence on rainfed agricultural production makes Africa more vulnerable to climate change effects.
- Food insecurity is more visible in Africa.
- Weather information and services are essential for farmers to more effectively survive the increasing occurrence of extreme weather events [2].

PROBLEM STATEMENT

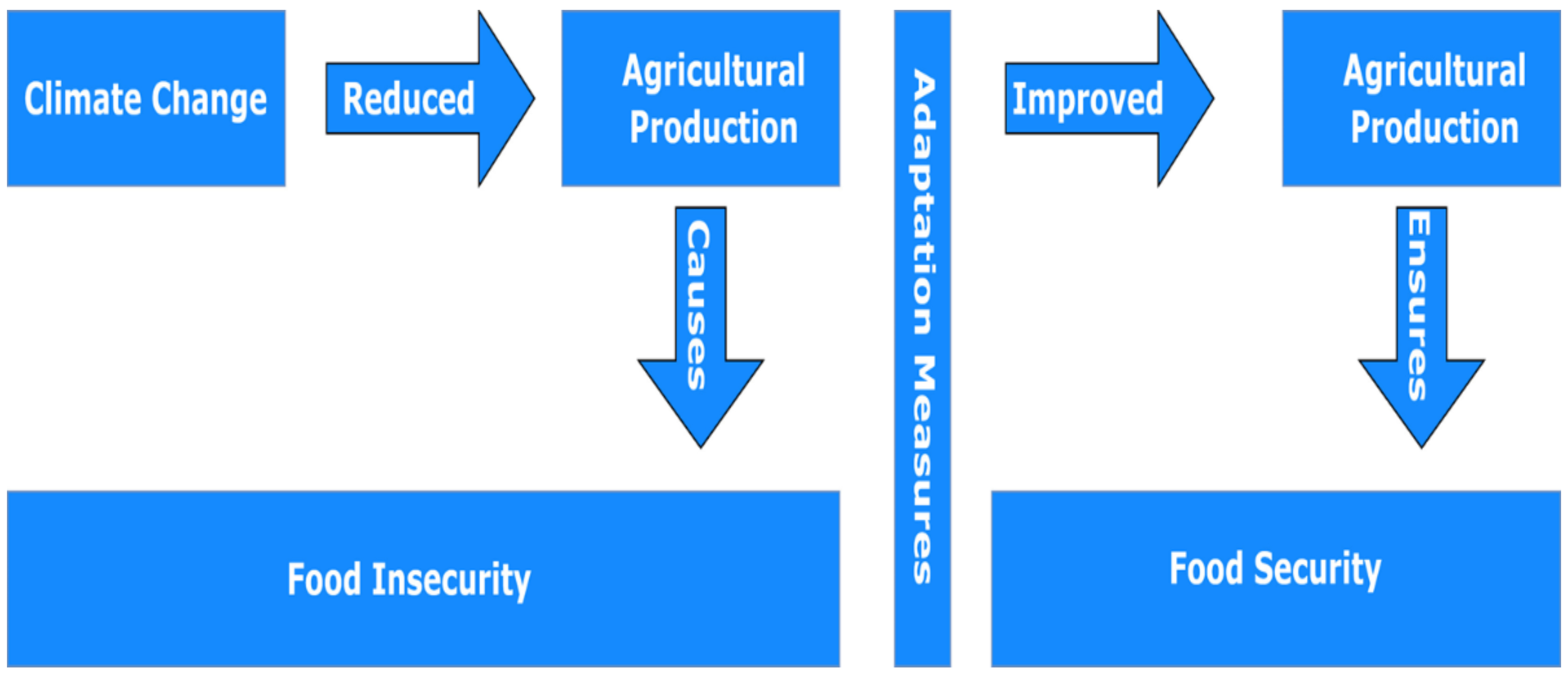

Figure 1. A block diagram summarizing effects of climate change on food security.

- Declining and highly unreliable rainfall, rising temperatures, rampant water scarcity, intense and prolonged droughts, crop diseases and exacerbated desertification process [3].

OBJECTIVES

- The main objective of this study was to develop Machine Learning (ML)-based models adapted to the context of daily weather forecasting in Senegal (Rainfall, Relative Humidity, and Maximum and Minimum Temperature).
- Spatial weather distribution.
- Annual weather cycle.

MATERIALS & METHODS

- In this study, ten ML regressors: Light Gradient Boosting Machine, CatBoost Regressor, Gradient Boosting Regressor, Extreme Gradient Boosting, Random Forest Regressor, Orthogonal Matching Pursuit, Extra Trees Regressor, K-Neighbors Regressor, AdaBoost Regressor, and Decision Tree Regressor were compared with stacked Ensemble Model.
- The study was implemented using the Knowledge Discovery in Databases process. Evaluation of models was done using Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE) and Coefficient of Determination (R^2)

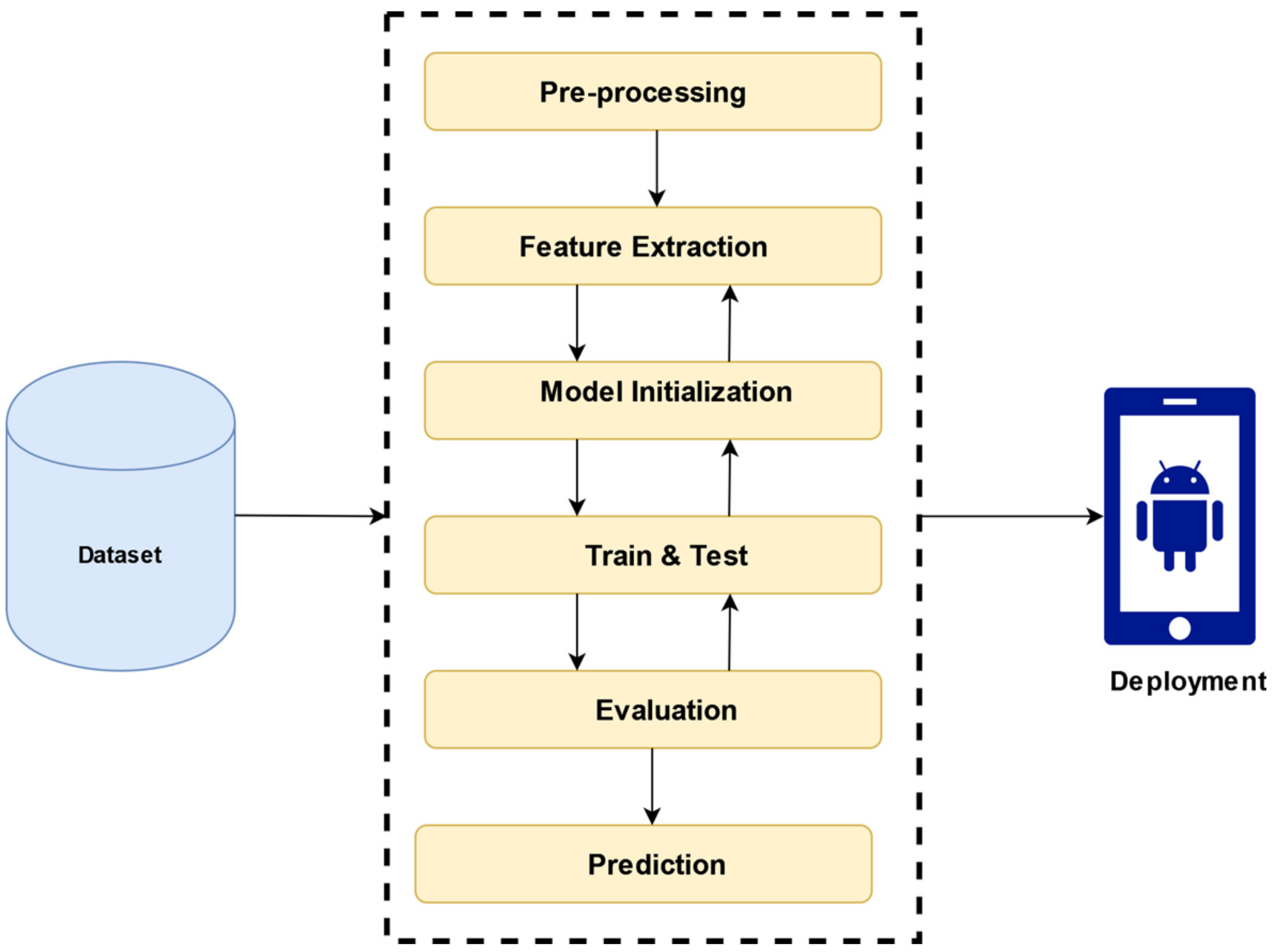

Figure 2. Workflow and experimental setup to construct the ML-based methodology for weather forecasting.

Table 1. Model performance for Relative Humidity Forecasting.

Model	MAE	MSE	RMSE	R^2
Ensemble Model	4.0126	29.9885	5.4428	0.9335
Light Gradient Boosting Machine	4.0693	30.6936	5.5040	0.9317
CatBoost Regressor	4.0619	30.7052	5.5046	0.9317
Gradient Boosting Regressor	4.0863	30.8061	5.5140	0.9314
Extreme Gradient Boosting	4.1601	32.1831	5.6292	0.9280
Random Forest Regressor	4.2284	32.9041	5.7005	0.9270
Orthogonal Matching Pursuit	4.2385	33.1158	5.7223	0.9268
Extra Trees Regressor	4.2533	33.3111	5.7349	0.9260
K Neighbors Regressor	4.4810	36.5971	6.0138	0.9184
AdaBoost Regressor	5.7023	48.4746	6.9384	0.8954
Decision Tree Regressor	5.9400	65.2236	8.0390	0.8553

Table 2. Model performance for Minimum Temperature Forecasting.

Model	MAE	MSE	RMSE	R^2
Ensemble Model	0.7908	1.1329	1.0515	0.9018
Gradient Boosting Regressor	0.7953	1.1481	1.0582	0.9006
Light Gradient Boosting Machine	0.7966	1.1508	1.0595	0.9004
CatBoost Regressor	0.7983	1.1554	1.0614	0.9001
Extreme Gradient Boosting	0.8107	1.1893	1.0771	0.8971
Orthogonal Matching Pursuit	0.8199	1.2034	1.0840	0.8956
Random Forest Regressor	0.8248	1.2200	1.0922	0.8942
Extra Trees Regressor	0.8301	1.2326	1.0982	0.8931
K Neighbors Regressor	0.8793	1.3646	1.1573	0.8815
AdaBoost Regressor	0.8961	1.4137	1.1727	0.8787
Decision Tree Regressor	1.1877	2.4335	1.5515	0.7865

Table 3. Model performance for Maximum Temperature Forecasting.

Model	MAE	MSE	RMSE	R^2
Ensemble Model	1.2515	2.8038	1.6591	0.8205
Light Gradient Boosting Machine	1.2618	2.8418	1.6694	0.8176
Gradient Boosting Regressor	1.2678	2.8478	1.6725	0.8175
CatBoost Regressor	1.2624	2.8501	1.6716	0.8171
Extreme Gradient Boosting	1.2878	2.9636	1.7031	0.8095
Random Forest Regressor	1.3031	3.0114	1.7195	0.8071
Extra Trees Regressor	1.3116	3.0473	1.7298	0.8048
Orthogonal Matching Pursuit	1.3240	3.1079	1.7519	0.8016
K Neighbors Regressor	1.3811	3.3403	1.8128	0.7865
AdaBoost Regressor	1.4331	3.3870	1.8281	0.7841
Decision Tree Regressor	1.8775	6.1235	2.4593	0.6098

Table 4. Model performance for Rainfall Forecasting.

Model	MAE	MSE	RMSE	R^2
Ensemble Model	0.2142	0.1681	0.4100	0.7733
CatBoost Regressor	0.2150	0.1691	0.4112	0.7719
Light Gradient Boosting Machine	0.2146	0.1695	0.4117	0.7714
Gradient Boosting Regressor	0.2221	0.1752	0.4185	0.7638
Extreme Gradient Boosting	0.2178	0.1752	0.4185	0.7638
Random Forest Regressor	0.2212	0.1797	0.4238	0.7578
Extra Trees Regressor	0.2246	0.1851	0.4302	0.7504
K Neighbors Regressor	0.2316	0.2022	0.4496	0.7272
AdaBoost Regressor	0.3803	0.2851	0.5325	0.6147
Orthogonal Matching Pursuit	0.4127	0.3336	0.5775	0.5502
Decision Tree Regressor	0.2910	0.3452	0.5875	0.5343

References

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 nyasulu.chimango@ugb.edu.sn