Estimating Poverty using Satellite Imagery and Machine Learning:
a Revolutionizing Approach for Policy-Makers

Preliminary Report

March 2023

Contents

Summary

Understanding the poverty situation is of utmost importance for policymakers from both government and non-government agencies, as poverty estimation is crucial to measure the effectiveness of national programs and guide the country's development strategy in an ever-changing economic landscape. Identifying the most vulnerable population is vital in determining resource allocation to achieve Sustainable Development Goals (SDGs) and disaster management. To achieve this, the Bangladesh Bureau of Statistics (BBS), in consultation with the Prime Minister's Office's Principal Coordinator for Sustainable Development Goal Affairs (PMO) and senior officials from various line ministries, recognized the need for more frequent geographically disaggregated estimation of poverty, enabling the government to target its policies more effectively.

Under the technical supervision of the SDG Coordinator's Office, the BBS implemented an exercise for poverty estimation using satellite image data under the Data4Now initiatives with support from the UN Statistics Division, A2i, and UN Data Group, and University of Southampton, coordinated by the UN Resident Coordinator's Office, Bangladesh. The initiative developed a poverty estimation model using freely available satellite imagery and Nighttime Light (NTL) data, which was validated with the 2016 Household and Income Expenditure Survey (HIES) data, achieving an accuracy of 84%. During the exercise, the team estimated poverty for 2022 using a square grid of 3890x3890 square meters, providing poverty estimates up to the union level, with the estimated national average of poverty at 19.0 in 2022.

BBS organized a knowledge-sharing event on 30 March 2023, to present the methodology and results of this innovative poverty estimation model, which uses big data and satellite images to assess poverty levels upto union level. The model's accuracy level can be further enhanced by incorporating additional data such as POI, land cover maps, road maps, and division headquarters location data, among others.

During the event, it was highlighted that this new methodology will enable policymakers to access more frequent and comprehensive poverty estimates, aiding in decision-making and resource allocation to achieve SDGs and disaster management. By adopting this new methodology, the BBS can make significant strides in improving the accuracy and relevance of poverty estimation in Bangladesh, particularly during survey interval periods.

<u>Key initiatives under Data4Now:</u> Two capacity development training workshops were organized in 2022 to carry out the poverty estimation using satellite images and a cloud-based platform. A total of 25 officials from BBS, Bangladesh Bank, General Economics Division, Finance Division, Bangladesh Telecommunication Regulatory Commission, and others received training.

While running the model three types of data (raster, vector, and tabular data) were needed. The VIIRS Cloud Mask–Outlier Removed (vcm–orm) annual composite NPP-VIIRS DNB data collected from the National Oceanic and Atmospheric Administration's National Centers for Environmental Information (NOAA/NCEI) of the United States were used to reflect the NTL intensity in Bangladesh. The moderate-resolution satellite image (January 2016) from Sentinel 2 was collected from the United States Geological Survey (USGS). Both raster data are freely available. Bangladesh district and upazila level administrative data were also collected and used as input to the model and poverty data (as tabular) estimated using the ELL method for 2016 from HIES survey was also incorporated into this model.

A grid-based image (approx. 30,000 nos) processing was utilized using R (programming language) and Google Earth Engine (GEE). Advanced machine learning techniques using Python were incorporated to estimate poverty in Bangladesh. By combining satellite imagery, machine learning algorithms, and poverty data, a Random Forest (RF) based Convolutional Neural Network (CNN) model was fitted using the training samples from the HIES 2016 poverty data. Then, ELL-based poverty estimation in 2016 was compared to the RF-based CNN model for the validated samples for accuracy assessment.

Seven types of layers were used in feature extraction, where out of 63617923 numbers of parameters, 5246979 were trainable, and 58370944 were non-trainable. Fifty epochs were used in the RF-based model to fit the model with poverty estimation using the ELL method with the HIES 2016 data and the accuracy of the feature extraction was 71%. Therefore, the model accuracy was 84 percent while running the code on the validation data. A data trend line indicating value concentration with the line along with distribution of poverty rate is shown here. A comparative statistics and maps for satellite and HIES maps are also shown in the report. According to this model, the estimated national average of poverty for 2022 is 19.0 where the lowest mean is recorded for Khulna division (18.3) and the highest is Barishal (20.0). Therefore, this model could be used for estimating the poverty situation in any inter-survey period, where sometimes the survey takes time to initiate timely.

Incorporating POI data, a land cover map, a road map, division headquarter location data, and other relevant ancillary data into the poverty estimation model can improve the accuracy and comprehensiveness of poverty estimates. Adopting this new model will enable BBS to provide policymakers with more frequent poverty estimates, which can assist in making informed decisions.

Photo: 2nd Workshop at Sarah Resort Gazipur.

Introduction

Poverty is a pressing issue for policymakers in both the government and non-government sectors. To allocate resources towards achieving the Sustainable Development Goals and improving quality of life, it is critical to understand the poverty situation. However, measuring poverty is not a straightforward task, especially in developing countries where traditional data sources like Demographic and Health Surveys and Household Income and Expenditure Surveys are still relied upon. Unfortunately, conducting these surveys frequently can be challenging due to time, money, and labor constraints, which makes it difficult to regularly monitor poverty.

Poverty is a multi-dimensional and complex phenomenon that cannot be accurately measured by relying on just one type of data. As a result, many researchers are developing various models to measure poverty on a smaller scale. To monitor poverty regularly, non-traditional data sources are being utilized in these models. Examples of such data sources include nighttime light (NTL) data, Google satellite imagery, land cover maps, road maps, division headquarters location data, and other related data. By using these alternative data sources in combination with traditional data, researchers are better able to measure poverty and track changes over time. This approach is particularly important for monitoring development and ensuring that resources are allocated to those who need them most. By developing more accurate poverty measures, policymakers and development organizations can make informed decisions and take targeted actions towards poverty reduction.

Under the technical supervision of the SDG Coordinator's Office, the Bangladesh Bureau of Statistics (BBS) implemented an exercise for poverty estimation using satellite image data with support from A2i, UN Data Group, and University of Southampton which was coordinated by UN Resident Coordinator's Office, Bangladesh. Two capacity development training workshops were organized regarding this exercise and more than 25 officials including 15 BBS officials attended these two workshops. This exercise aims to develop a poverty estimation model using satellite imageries (freely available) and nighttime light data, which was validated with the 2016 HIES data and will run validation with the HIES 2022. It was not possible to validate the 2010 data for lack of available satellite images/data.

To present the methodology and of this innovative poverty estimation model, BBS organized a knowledge-sharing event on 30 March 2023. The innovative poverty estimation model, which uses big data and satellite images to assess poverty levels upto union level. The model's accuracy level can be further enhanced by incorporating additional data such as POI, land cover maps, road maps, and division headquarters location data, among others.

During the event, it was highlighted that this new methodology will enable policymakers to access more frequent and comprehensive poverty estimates, aiding in decision-making and resource allocation to achieve SDGs and disaster management. By adopting this new methodology, the BBS can make significant strides in improving the accuracy and relevance of poverty estimation in Bangladesh, particularly during survey interval periods.

Overall, the development of more accurate poverty measures is crucial for policymakers and development organizations to make informed decisions and take targeted actions towards poverty reduction. By implementing this new methodology, the BBS can make significant strides in improving the accuracy and relevance of poverty estimation in Bangladesh, particularly during survey interval periods.

Aim of the Exercise

This exercise aims to develop a poverty estimation model using non-traditional data such as satellite imageries (freely available) and nighttime light data for 2022 and validate it against Household Income Expenditure Survey 2022. Afterwards, check the accuracy of the small area estimation of the proposed model.

The objective of this exercise was to strengthen the ability of national statistical systems to produce better and more timely data to inform policies and monitor progress towards achieving the SDGs Bangladesh, with a focus on the SDG indicator 1.2.1, aims to strengthen its statistical systems by leveraging data innovations and better integrating geospatial and statistical operations. This will enable the country to prioritize its goals and track progress effectively, ultimately leading to the successful achievement of the SDGs.

Study area

Bangladesh is a densely populated country located in South Asia. Almost a quarter of its population lives below the poverty line. The land area of Bangladesh is 147570 square kilometers, with most of the land used for agriculture or located near rivers. Unfortunately, Bangladesh is prone to various natural disasters such as floods, droughts, cyclones, and riverbank erosions. Due to these challenges, people in Bangladesh struggle to find ways to live and survive. The country has eight administrative divisions and 64 districts, which are further divided into 577 Upazilas (figure 1). To give you a better idea of where Bangladesh is located, please refer to figure 2.

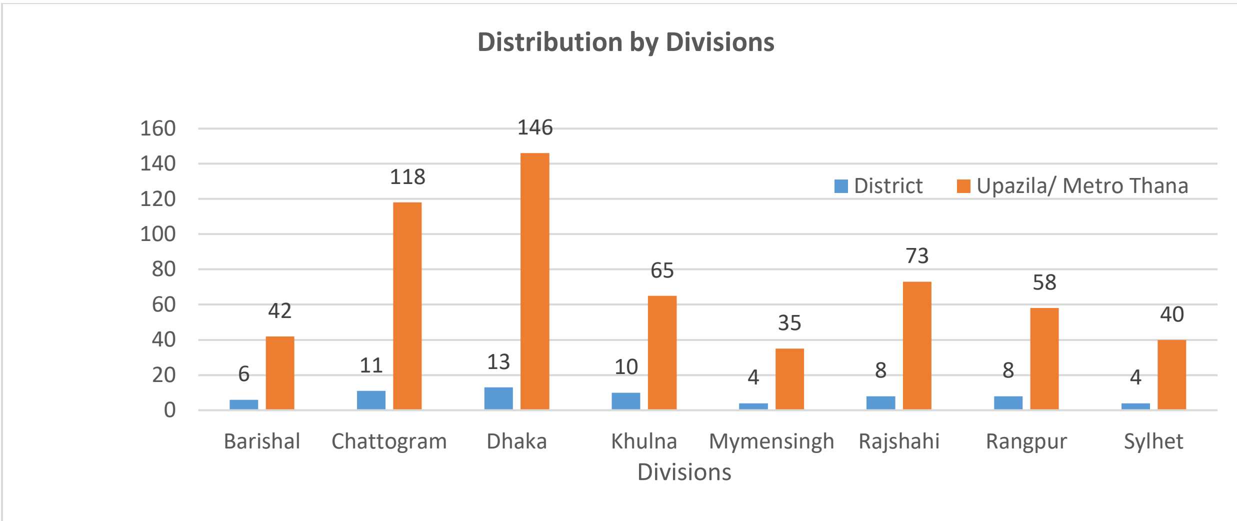

Figure 1: Number of Divisions, Districts and Upazilas distribution in Bangladesh

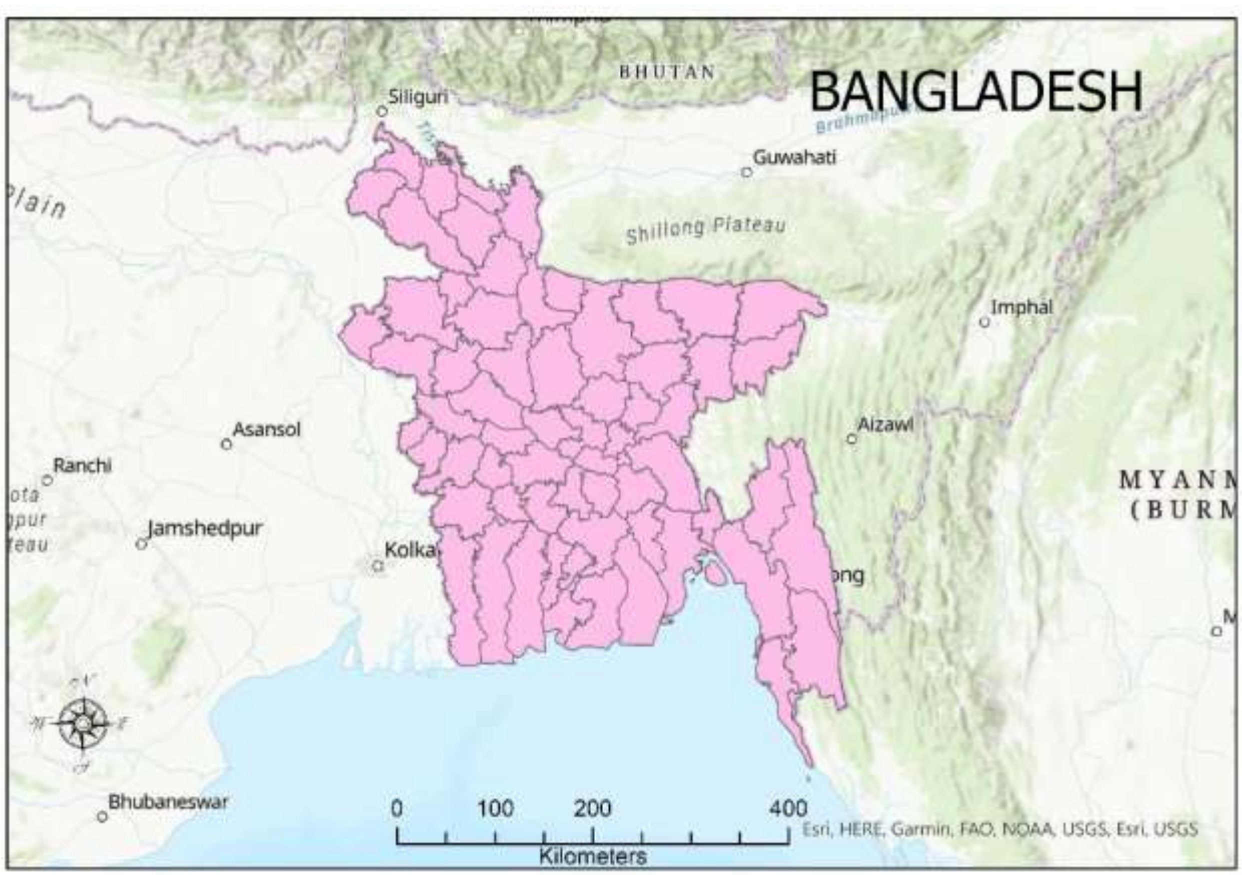

Figure 2: Location map of Bangladesh and its surrounding areas.

Data

The poverty estimation model mainly depends on non-traditional data where the data is freely available. Three data types, raster, vector, and tabular data are needed to input into the model. The VIIRS Cloud Mask–Outlier Removed (vcm–orm) annual composite NPP-VIIRS DNB data collected from the National Oceanic and Atmospheric Administration's National Centers for Environmental Information (NOAA/NCEI) of the United States were used to reflect the NTL intensity in Bangladesh. Figure 3 shows the NTL data used in the proposed model. The information on the NTL data is given below:

Field 1: VIIRS SDR or Product that made the composite "SVDNB"

Field 2: satellite name "npp "

Field 3: date range "20160101-20161231 "

Field 4: ROI "75N060E"

Field 5: config short name "vcmcfg"

Field 6: version "v10" is version 1.0.

Field 7: creation date 201807311200: avg_rade9

Figure 3: Nighttime Light data used in the proposed model.

Bangladesh District and Upazila level administrative data as vector data and upper poverty line data estimated using the ELL method from Household Income and Expenditure Survey (2016) as tabular data were also collected and used as input to the model.

Methodology

Poverty mapping methodology is the ELL method developed by Elbers et al using Small Area Estimation (SAE) techniques The ELL method, which has been widely tested and validated around the world, takes advantage of the strengths of both sources of data used in such exercises. Alternative methods have taken place as ELL methods need the help of long surveys which occur in a greater interval period. To monitor poverty regularly, non-traditional data sources are being utilized in these models. Examples of such data sources include nighttime light (NTL) data, Google satellite imagery, land cover maps, road maps, division headquarters location data, and other related data. World bank has used high resolution satellite imagery for estimating economic wellbeing in Sri Lanka. Similarly, ADB also mapped the spatial distribution of Poverty using satellite imagery in Thailand.

Characteristics of Satellite Image based poverty estimation:

- No usage of traditional data (such as Census, Survey, etc.)
- Uses of Satellite Images (Open data source)
- Uses of Night Time Light Data (Development Indicators)
- Quick Calculation with High Accuracy
- Need very high computational cost (e.g., High configured Server, High bandwidth Internet connection)

Firstly, a grid (3840 X 3840 meters) was created for the whole of Bangladesh and found out that 9555 grids along with the centre point of each grid (figure 4).

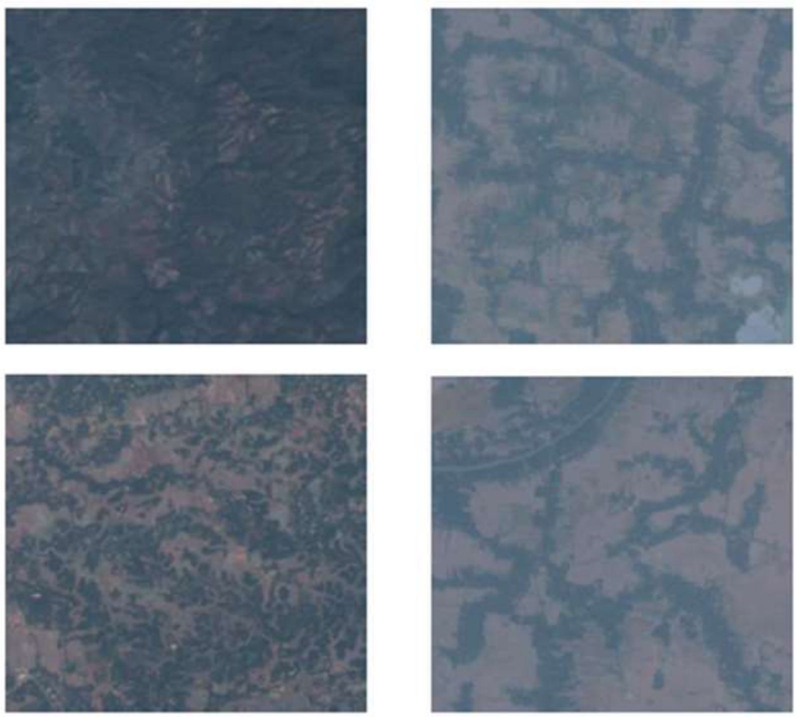

Figure 4: examples of Grid images of Sentinel 2

Programming R informs that Rstudio was used to create the centre points, and all the grid centre points were imported into Google Earth Engine (GEE) to download Sentinel 2 images maintaining the grid size and locations; afterwards, Google Drive was used to store the grid images. A Convolution Neural Network (CNN) algorithm (figure 5) was used to extract the physical feature from the images.

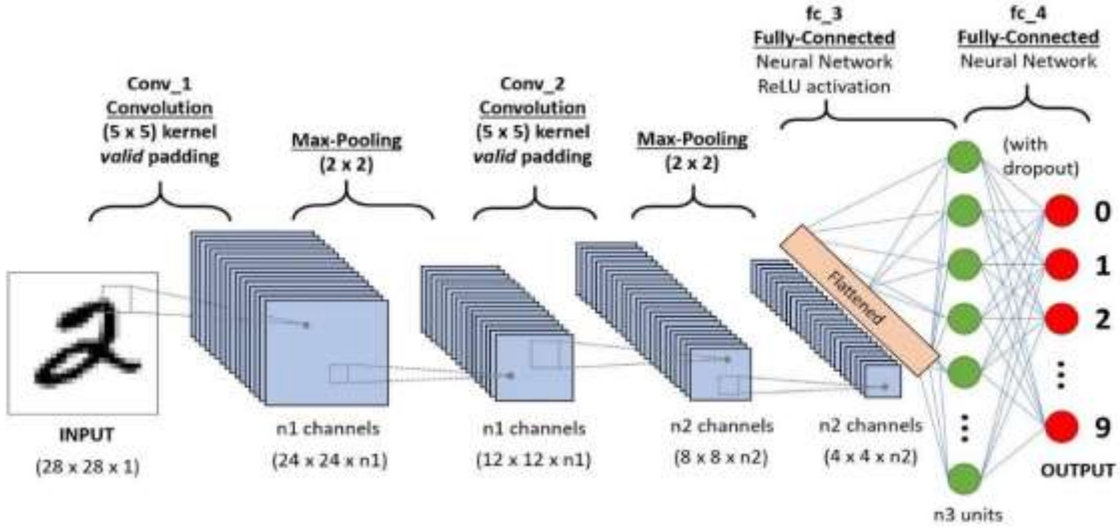

Figure 5: A schematic overview of the Convolution Neural Network.

(Source: https://paperswithcode.com/methods/category/convolutional-neural-networks)

Prediction of nighttime light intensity is discarded, and the trained CNN alone is used to summarize the complex multidimensional input of image data into a single vector. This vector has hundreds of features, each assigned a single value in every image. These features are a representation of what the network detects in a snap. They have several advantages over raw pixel values, most notably that convolutional layers scan over the image using kernels so that it does not matter where features are placed on the image.

At the same time, nighttime light (NTL) data also was incorporated inside the CNN model to develop the Random Forest (RF) based CNN model. Poverty estimation data (Direct estimation from HIES 2016) was also included in the RF-based CNN model to train the model with 60 per cent grids. Afterwards, the RF-based CNN model was applied to the rest of the 40 per cent grids to predict the poverty estimation. Therefore, ELL-based poverty estimation in 2019 was compared to the RF-based CNN model for accuracy assessment. A flowchart (figure 6) of the RF-based CNN model to estimate Poverty is illustrated below.

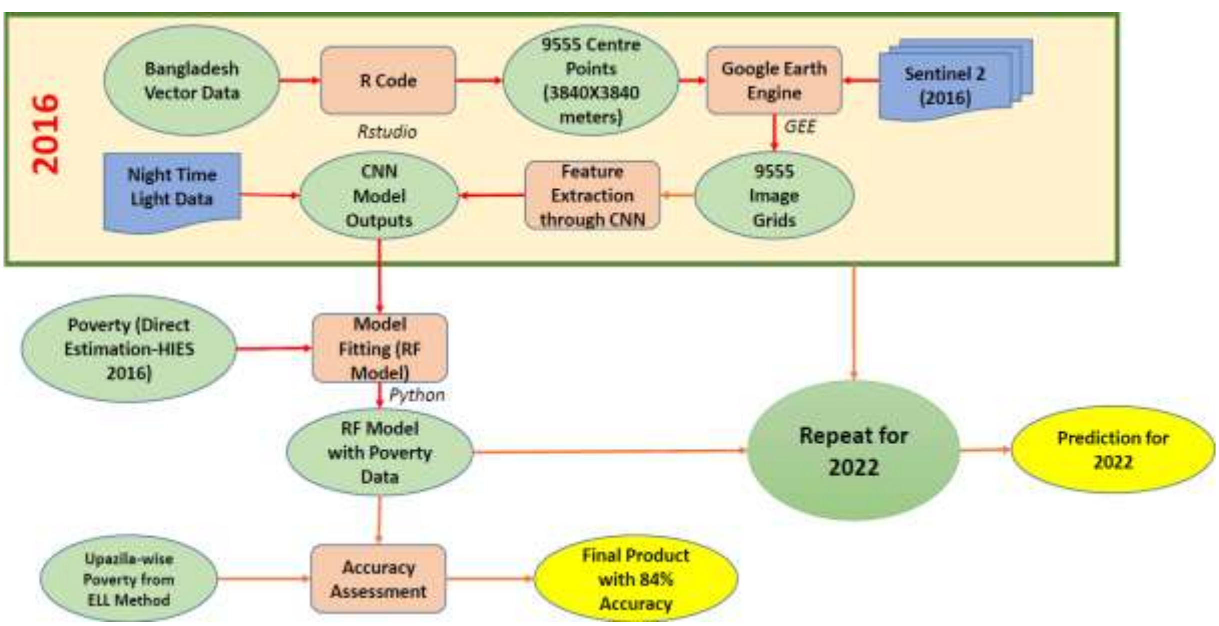

Figure 6: A flowchart of the RF-based CNN model to estimate Poverty.

Results

Seven types of layers were used in feature extraction, where out of 63617923 numbers of parameters, 5246979 were trainable, and 58370944 were non-trainable. Figure 7 shows the type of layer used in feature extraction with the number of parameters.

```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 resnet152 (Functional)      (None, 2048)              58370944

 dropout_13 (Dropout)        (None, 2048)              0

 dense_19 (Dense)            (None, 2048)              4196352

 flatten_6 (Flatten)         (None, 2048)              0

 dropout_14 (Dropout)        (None, 2048)              0

 dense_20 (Dense)            (None, 512)               1049088

 dense_21 (Dense)            (None, 3)                 1539

=================================================================
Total params: 63,617,923
Trainable params: 5,246,979
Non-trainable params: 58,370,944
_________________________________________________________________
```

Figure 7: Type of layers used in feature extraction with the number of parameters.

Fifty epochs were used in the RF-based model to fit the model with the poverty estimation using the ELL method with the HIES 2016 data. Figure 8(a,b) shows the number of epochs run in the model, and the accuracy of the feature extraction was 71%. This was again repeated for 2022 predictions.

```
244/244 [==============================] - 1310s 5s/step - loss: 0.7218 - accuracy: 0.7167
Epoch 41/50
244/244 [==============================] - 1320s 5s/step - loss: 0.7196 - accuracy: 0.7167
Epoch 42/50
244/244 [==============================] - 1326s 5s/step - loss: 0.7208 - accuracy: 0.7167
Epoch 43/50
244/244 [==============================] - 1331s 5s/step - loss: 0.7192 - accuracy: 0.7167
Epoch 44/50
244/244 [==============================] - 1321s 5s/step - loss: 0.7198 - accuracy: 0.7167
Epoch 45/50
244/244 [==============================] - 1314s 5s/step - loss: 0.7190 - accuracy: 0.7167
Epoch 46/50
244/244 [==============================] - 1310s 5s/step - loss: 0.7202 - accuracy: 0.7167
Epoch 47/50
244/244 [==============================] - 1323s 5s/step - loss: 0.7222 - accuracy: 0.7167
Epoch 48/50
244/244 [==============================] - 1326s 5s/step - loss: 0.7175 - accuracy: 0.7165
Epoch 49/50
244/244 [==============================] - 1325s 5s/step - loss: 0.7212 - accuracy: 0.7167
Epoch 50/50
244/244 [==============================] - 1335s 5s/step - loss: 0.7192 - accuracy: 0.7167
```

Figure 8(a): Epochs in a nutshell.

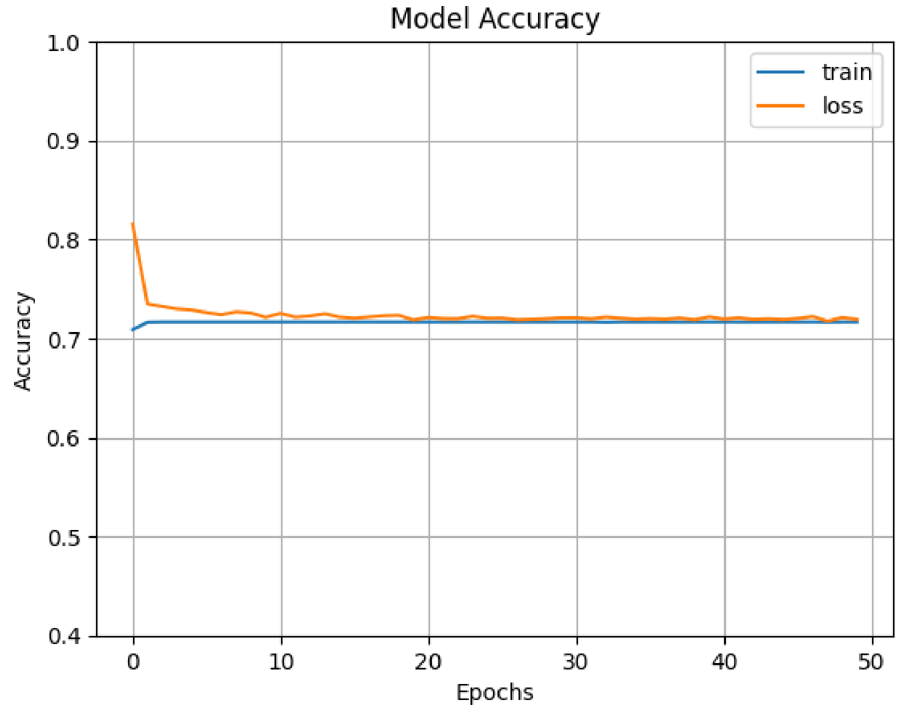

Figure 8 (b): Feature extraction model accuracy, and the accuracy was 71%.

Therefore, the model accuracy was 84 per cent while running the code on the validation data. Figure 9 shows the code used for validation data estimation of Poverty.

```
print("RMSE: ", np.sqrt(mean_squared_error(ya, ya_hat)))
print("R2: ", str(int(r2_score(ya, ya_hat)*100))+'%')

RMSE:  0.06531708067448559
R2:  84%
```

Figure 9: Code used for validation, RMSE, and R2 shows the model accuracy.

The distribution of poverty rate and the data trend line, which indicates the value concentrations with the line is shown in the following figures:

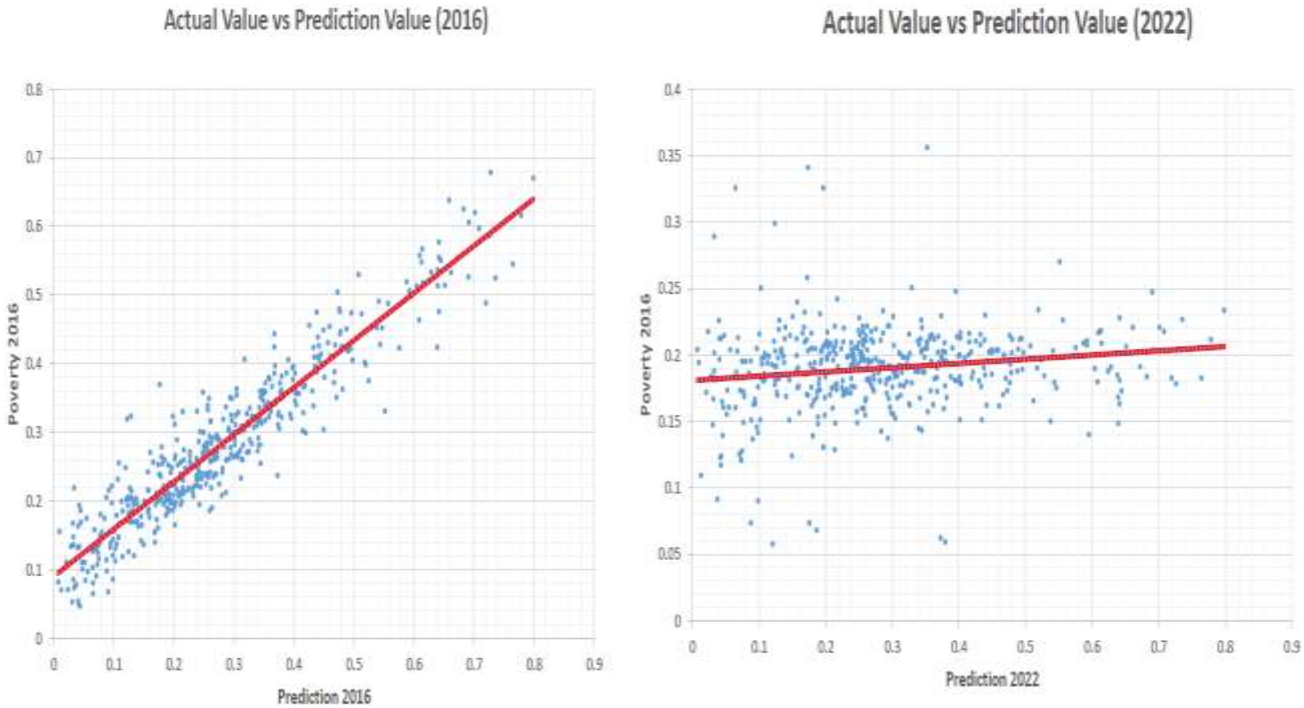

Figure 10: Distribution of Poverty (Predicted)

The distribution of predicted poverty can be found from the following table:

Division	Min	Max	Mean
Barishal	15.38	24.59	19.06
Chattogram	15.13	25.06	20.08
Dhaka	7.37	34.10	19.20
Khulna	6.82	35.62	18.88
Mymensingh	5.94	23.32	18.33
Rajshahi	5.78	23.10	18.55
Rangpur	14.01	24.73	18.89
Sylhet	15.96	22.64	19.73
		National	**19.00**

Table 1: Distribution of Estimated Poverty 2022

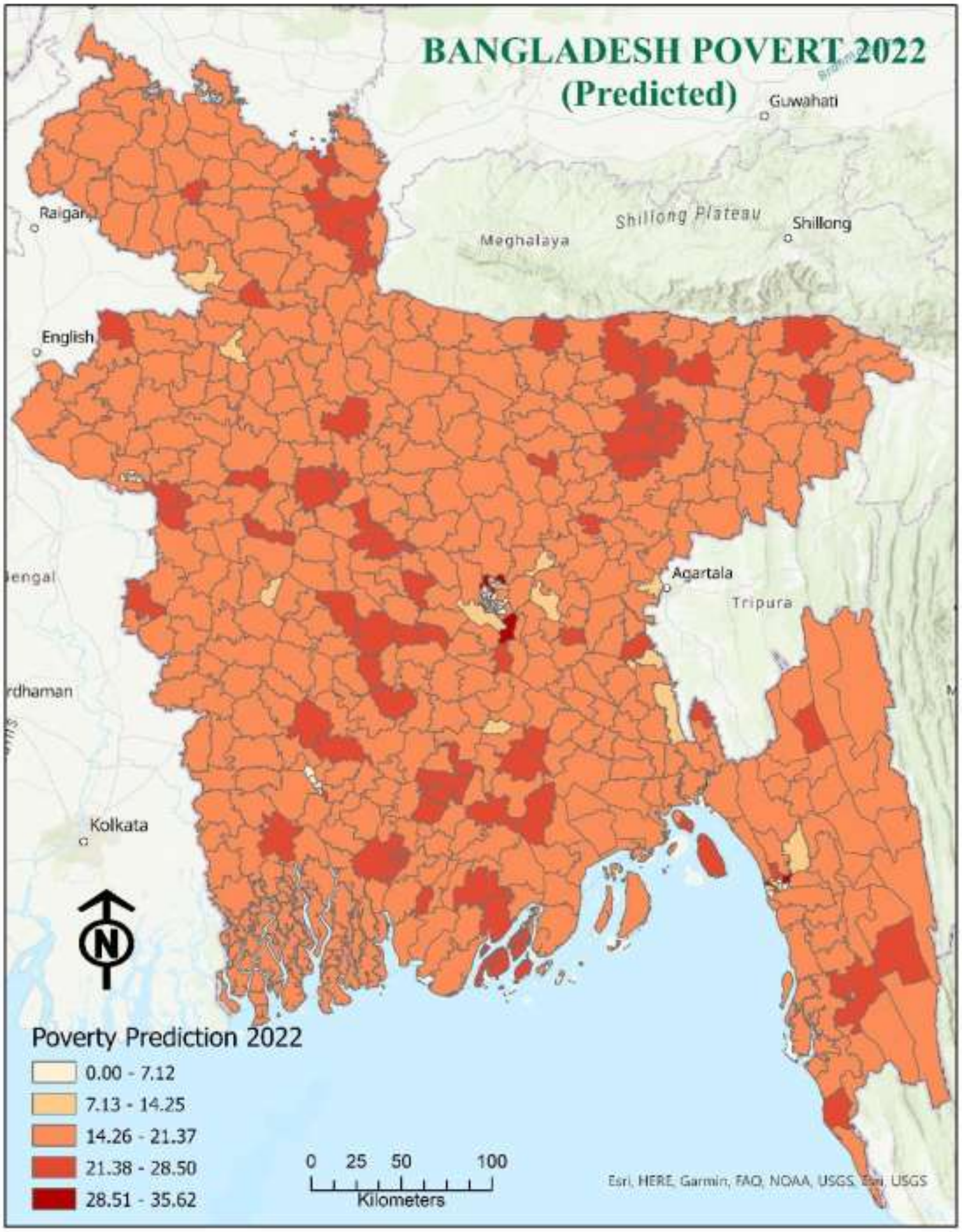

Figure 11: Bangladesh poverty 2022 (predicted)

The following Map shows the final output of the prediction model (RF-based CNN model using satellite images and NTL data.

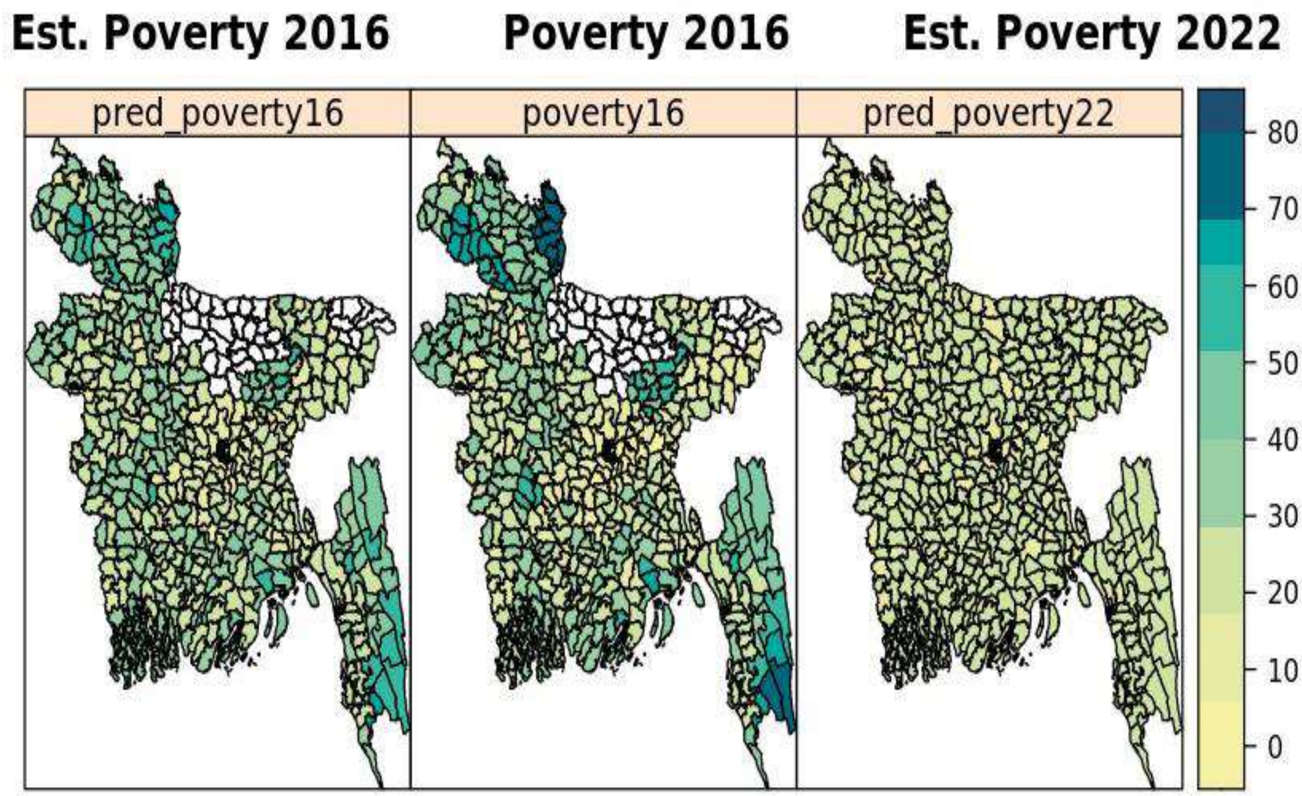

Figure 12: Poverty 2016 (ELL Method), Poverty 2016 (RF Model) and Predicted Poverty 2022

Conclusion

The proposed model was designed with an RF-based CNN model for feature extraction, which has a very high geo computational cost, and any normal personal workstation could not perform the task. Following recommendations will increase the model's efficiency:

- Reduce the Spatial Grid Size (<2 km) to increase accuracy rate.
- Incorporate possible ancillary data in the RF Model and feature extraction.

Satellite imagery is a potentially valuable alternative data source to enhance the granularity of poverty statistics compiled from household surveys. This poverty estimation model can provide more accurate and comprehensive estimates of poverty if POI data, land cover map, road map, and division headquarter location data with other ancillary data are incorporated. This model can also be endorsed as an official statistic for non-survey/ interval periods.

গণপ্রজাতন্ত্রী বাংলাদেশ সরকার
বাংলাদেশ পরিসংখ্যান ব্যুরো
এসডিজি সেল
পরিসংখ্যান ভবন, ই-২৭/এ আগারগাঁও, ঢাকা-১২০৭

নং: ৫২.০১.০০০০.০০০.৯৯.০০১.২১.৩৬

তারিখ: ১৬ বৈশাখ ১৪২৮ / ২৯ এপ্রিল ২০২১

বিষয়: UNSD'র সহায়তায় 'Data4Now' শীর্ষক উদ্যোগের আওতায় উদ্ভাবনী পদ্ধতিতে এসডিজি সূচক ১.২.১-এর উপাত্ত প্রস্তুতের পাইলটিং সংক্রান্ত ওয়ার্কিং টিম গঠন।

উপর্যুক্ত বিষয়ের পরিপ্রেক্ষিতে মহোদয়কে জানানো যাচ্ছে যে, UNSD'র কারিগরি সহায়তায় উদ্ভাবনী পদ্ধতিতে এসডিজি'র উপাত্ত প্রস্তুত বিষয়ে সক্ষমতা বৃদ্ধিতে বাংলাদেশ পরিসংখ্যান ব্যুরো ও এটুআই প্রোগ্রাম যৌথভাবে 'Data4Now (D4N)' শীর্ষক উদ্যোগ বাস্তবায়ন করছে। এ উদ্যোগের মাধ্যমে টেকসই উন্নয়ন অভীষ্ট অর্জনের অগ্রগতি পরিবীক্ষণে স্থানীয় ও জাতীয় নীতিনির্ধারকদের প্রয়োজনীয় তথ্য সরবরাহে উদ্ভাবনী পদ্ধতি ব্যবহারের সক্ষমতা বৃদ্ধি, সম্ভাব্যতা যাচাই ও বাস্তব ক্ষেত্রে তার প্রয়োগের পাইলটিং করা হবে। 'Data4Now (D4N)' শীর্ষক উদ্যোগের আওতায় এসডিজি সূচক ১.২.১ পাইলটিং-এর জন্য নিম্নবর্ণিত একটি ওয়ার্কিং টিম গঠন করা হলো:

ক্রমিক	নাম, পদবি ও কর্মস্থল	টিমে দায়িত্ব
১	ড. দিপংকর রায়, প্রকল্প পরিচালক (উপসচিব), HIES প্রকল্প, বিবিএস	টিম লিডার
২	জনাব মহিউদ্দিন আহমেদ, উপপ্রকল্প পরিচালক, HIES প্রকল্প, বিবিএস	সদস্য
৩	জনাব মো. আবদুল লতিফ, উপপরিচালক, HIES প্রকল্প, বিবিএস	সদস্য
৪	জনাব নাঈমা আকতার, উপপরিচালক, এসডিজি সেল, বিবিএস	সদস্য
৫	জনাব মোহাম্মদ জুনাঈদ ভূঁইয়া, পরিসংখ্যান কর্মকর্তা, ইন্ডাস্ট্রি অ্যান্ড লেবার উইং, বিবিএস	সদস্য
৬	জনাব মো. মাহাবুব আলম, পরিসংখ্যান কর্মকর্তা, ডেমোগ্রাফি অ্যান্ড হেলথ উইং, বিবিএস	সদস্য
৭	জনাব ফাহমিদা ফেরদৌস, পরিসংখ্যান কর্মকর্তা, সেন্সাস উইং, বিবিএস	সদস্য
৮	জনাব সামি কবির, প্রোগ্রামার, বাংলাদেশ পরিসংখ্যান ব্যুরো	সদস্য
৯	প্রতিনিধি, সাধারণ অর্থনীতি বিভাগ (সিনিয়র সহকারী সচিব ও তদূর্ধ্ব পর্যায়ের)	সদস্য
১০	প্রতিনিধি, অর্থ বিভাগ (সিনিয়র সহকারী সচিব ও তদূর্ধ্ব পর্যায়ের)	সদস্য
১১	প্রতিনিধি, পরিসংখ্যান ও তথ্য ব্যবস্থাপনা বিভাগ (সিনিয়র সহকারী সচিব ও তদূর্ধ্ব পর্যায়ের)	সদস্য
১২	প্রতিনিধি, বাংলাদেশ টেলিকমিউনিকেশন রেগুলেটরি কমিশন (সিনিয়র সহকারী সচিব ও তদূর্ধ্ব পর্যায়ের)	সদস্য
১৩	প্রতিনিধি, এটুআই প্রোগ্রাম	সদস্য
১৪	প্রতিনিধি, বাংলাদেশ ব্যাংক (সিনিয়র সহকারী সচিব ও তদূর্ধ্ব পর্যায়ের)	সদস্য
১৫	প্রতিনিধি, জাতিসংঘের আবাসিক প্রতিনিধির কার্যালয়, ঢাকা	সদস্য
১৬	জনাব মো. আলমগীর হোসেন, ফোকাল পয়েন্ট কর্মকর্তা, এসডিজি সেল, বিবিএস	সদস্য-সচিব

০২। উল্লিখিত টিমের সদস্যবৃন্দ Data4Now (D4N) উদ্যোগের আওতায় এ সংক্রান্ত আয়োজিত প্রশিক্ষণ ও সেমিনারে অংশগ্রহণ করে সংশ্লিষ্ট বিষয়ে নিজেদের দক্ষতাকে ব্যবহারপূর্বক পাইলটিং কার্যক্রম বাস্তবায়ন করবেন।

০৩। বিশেষ প্রয়োজনে জনাব মো. আলমগীর হোসেন, উপপরিচালক ও ফোকাল পয়েন্ট কর্মকর্তা, এসডিজি সেল, বিবিএস ফোন: ০১৭৮৯-৯৪৪৯৪৪, ইমেইল: alamgir.hossen@bbs.gov.bd-এর সঙ্গে যোগাযোগ করা যেতে পারে।

29/04/2021

মোহাম্মদ তাজুল ইসলাম
(অতিরিক্ত সচিব)
মহাপরিচালক
ফোন: ০২-৫৫০০৭০৫৬
ইমেইল: dg@bbs.gov.bd

[অপর পৃষ্ঠা দ্রষ্টব্য]

Annex II Poverty Estimates for 2022

District Name	Upazila Name	Poverty Prediction for 2022	Average prediction value for District	
Barguna	Amtali	20	20.2	
Barguna	Bamna	25		
Barguna	Barguna Sadar	19		
Barguna	Betagi	18		
Barguna	Patharghata	19		
Barisal	Agailjhara	21	20.8	
Barisal	Babuganj	16		
Barisal	Bakerganj	19		
Barisal	Banari Para	24		
Barisal	Gaurnadi	21		
Barisal	Hizla	23		
Barisal	Barisal Sadar (Kotwali)	25		
Barisal	Mehendiganj	19		
Barisal	Muladi	19		
Barisal	Wazirpur	21		
Bhola	Bhola Sadar	23	19.9	
Bhola	Burhanuddin	19		
Bhola	Char Fasson	20		
Bhola	Daulatkhan	21		
Bhola	Lalmohan	16		
Bhola	Manpura	20		
Bhola	Tazumuddin	20		
Jhalokati	Jhalokati Sadar	20	19.5	
Jhalokati	Kanthalia	20		
Jhalokati	Nalchity	18		
Jhalokati	Rajapur	20		
Patuakhali	Bauphal	19	19.7	
Patuakhali	Dashmina	18		
Patuakhali	Dumki	19		
Patuakhali	Galachipa	22		
Patuakhali	Kala Para	21		
Patuakhali	Mirzaganj	17		
Patuakhali	Patuakhali Sadar	22		
Pirojpur	Bhandaria	18	19.6	
Pirojpur	Kawkhali	15		
Pirojpur	Mathbaria	19		
Pirojpur	Nazirpur	20		
Pirojpur	Pirojpur Sadar	21		
Pirojpur	Nesarabad (Swarupkati)	22		
Pirojpur	Zianagar	22		
Bandarban	Alikadam	20	20.7	
Bandarban	Bandarban Sadar	20		

Bandarban	Lama	22		
Bandarban	Naikhongchhari	20		
Bandarban	Rowangchhari	20		
Bandarban	Ruma	22		
Bandarban	Thanchi	21		
Brahamanbaria	Akhaura	13	18.4	
Brahamanbaria	Banchharampur	21		
Brahamanbaria	Bijoynagar	19		
Brahamanbaria	Brahmanbaria Sadar	20		
Brahamanbaria	Ashuganj	20		
Brahamanbaria	Kasba	20		
Brahamanbaria	Nabinagar	16		
Brahamanbaria	Nasirnagar	19		
Brahamanbaria	Sarail	18		
Chandpur	Chandpur Sadar	18	18.4	
Chandpur	Faridganj	18		
Chandpur	Haim Char	21		
Chandpur	Hajiganj	19		
Chandpur	Kachua	21		
Chandpur	Matlab Dakshin	14		
Chandpur	Matlab Uttar	18		
Chandpur	Shahrasti	18		
Chittagong	Anowara	17	19.2	
Chittagong	Bayejid Bostami	22		
Chittagong	Banshkhali	20		
Chittagong	Boalkhali	19		
Chittagong	Chandanaish	20		
Chittagong	Chandgaon	34		
Chittagong	Double Mooring	21		
Chittagong	Fatikchhari	20		
Chittagong	Halishahar	7		
Chittagong	Hathazari	15		
Chittagong	Kotwali	9		
Chittagong	Khulshi	13		
Chittagong	Lohagara	20		
Chittagong	Mirsharai	21		
Chittagong	Pahartali	33		
Chittagong	Patiya	20		
Chittagong	Patenga	21		
Chittagong	Rangunia	20		
Chittagong	Raozan	14		
Chittagong	Sandwip	23		
Chittagong	Satkania	18		
Chittagong	Sitakunda	15		
Comilla	Barura	17	19.3	
Comilla	Brahman Para	15		

Comilla	Burichang	26		
Comilla	Chandina	21		
Comilla	Chauddagram	14		
Comilla	Comilla Sadar Dakshin	20		
Comilla	Daudkandi	21		
Comilla	Debidwar	20		
Comilla	Homna	21		
Comilla	Comilla Adarsha Sadar	13		
Comilla	Laksam	20		
Comilla	Manoharganj	21		
Comilla	Meghna	18		
Comilla	Muradnagar	19		
Comilla	Nangalkot	20		
Comilla	Titas	23		
Cox'S Bazar	Chakaria	18	19.5	
Cox'S Bazar	Cox'S Bazar Sadar	21		
Cox'S Bazar	Kutubdia	21		
Cox'S Bazar	Maheshkhali	20		
Cox'S Bazar	Pekua	15		
Cox'S Bazar	Ramu	21		
Cox'S Bazar	Teknaf	18		
Cox'S Bazar	Ukhia	22		
Feni	Chhagalnaiya	16	17.5	
Feni	Daganbhuiyan	19		
Feni	Feni Sadar	15		
Feni	Fulgazi	16		
Feni	Parshuram	24		
Feni	Sonagazi	15		
Khagrachhari	Dighinala	20	20.4	
Khagrachhari	Khagrachhari Sadar	23		
Khagrachhari	Lakshmichhari	21		
Khagrachhari	Mahalchhari	19		
Khagrachhari	Manikchhari	20		
Khagrachhari	Matiranga	20		
Khagrachhari	Panchhari	20		
Khagrachhari	Ramgarh	20		
Lakshmipur	Kamalnagar	19	19.4	
Lakshmipur	Lakshmipur Sadar	17		
Lakshmipur	Roypur	21		
Lakshmipur	Ramganj	21		
Lakshmipur	Ramgati	19		
Noakhali	Begumganj	19	18.1	
Noakhali	Chatkhil	16		
Noakhali	Companiganj	17		
Noakhali	Hatiya	20		
Noakhali	Kabirhat	18		

Noakhali	Senbagh	20		
Noakhali	Sonaimuri	16		
Noakhali	Subarnachar	19		
Noakhali	Noakhali Sadar (Sudharam)	18		
Rangamati	Baghai Chhari	20	20.2	
Rangamati	Barkal	20		
Rangamati	Kawkhali (Betbunia)	19		
Rangamati	Belai Chhari	21		
Rangamati	Kaptai	20		
Rangamati	Jurai Chhari	19		
Rangamati	Langadu	21		
Rangamati	Naniarchar	20		
Rangamati	Rajasthali	21		
Rangamati	Rangamati Sadar	21		
Dhaka	Badda	18	18.1	
Dhaka	Biman Bandar	12		
Dhaka	Cantonment	36		
Dhaka	Demra	15		
Dhaka	Dhamrai	19		
Dhaka	Dohar	22		
Dhaka	Hazaribagh	29		
Dhaka	Kadamtali	18		
Dhaka	Khilgaon	7		
Dhaka	Khilkhet	12		
Dhaka	Keraniganj	11		
Dhaka	Mirpur	12		
Dhaka	Nawabganj	20		
Dhaka	Sabujbagh	9		
Dhaka	Savar	17		
Dhaka	Shahbagh	12		
Dhaka	Sher-e-bangla Nagar	25		
Dhaka	Tejgaon Ind. Area	12		
Dhaka	Turag	30		
Dhaka	Uttara	12		
Dhaka	Uttar Khan	33		
Faridpur	Alfadanga	19	19.4	
Faridpur	Bhanga	20		
Faridpur	Boalmari	18		
Faridpur	Char Bhadrasan	21		
Faridpur	Faridpur Sadar	22		
Faridpur	Madhukhali	18		
Faridpur	Nagarkanda	18		
Faridpur	Sadarpur	17		
Faridpur	Saltha	22		
Gazipur	Gazipur Sadar	15	18.4	
Gazipur	Kaliakair	18		

Gazipur	Kaliganj	20		
Gazipur	Kapasia	20		
Gazipur	Sreepur	19		
Gopalganj	Gopalganj Sadar	18	19.6	
Gopalganj	Kashiani	19		
Gopalganj	Kotali Para	19		
Gopalganj	Muksudpur	22		
Gopalganj	Tungi Para	20		
Jamalpur	Bakshiganj	16	18.6	
Jamalpur	Dewanganj	19		
Jamalpur	Islampur	20		
Jamalpur	Jamalpur Sadar	19		
Jamalpur	Madarganj	18		
Jamalpur	Melandaha	18		
Jamalpur	Sarishabari	20		
Kishoreganj	Austagram	21	19.8	
Kishoreganj	Bajitpur	21		
Kishoreganj	Bhairab	14		
Kishoreganj	Hossainpur	23		
Kishoreganj	Itna	23		
Kishoreganj	Karimganj	17		
Kishoreganj	Katiadi	18		
Kishoreganj	Kishoreganj Sadar	15		
Kishoreganj	Kuliar Char	27		
Kishoreganj	Mithamain	22		
Kishoreganj	Nikli	20		
Kishoreganj	Pakundia	17		
Kishoreganj	Tarail	20		
Madaripur	Kalkini	20	19.5	
Madaripur	Madaripur Sadar	20		
Madaripur	Rajoir	18		
Madaripur	Shib Char	20		
Manikganj	Daulatpur	19	19	
Manikganj	Ghior	15		
Manikganj	Harirampur	20		
Manikganj	Manikganj Sadar	22		
Manikganj	Saturia	20		
Manikganj	Shibalaya	20		
Manikganj	Singair	17		
Munshiganj	Gazaria	18	18.8	
Munshiganj	Lohajang	18		
Munshiganj	Munshiganj Sadar	17		
Munshiganj	Serajdikhan	16		
Munshiganj	Sreenagar	21		
Munshiganj	Tongibari	23		
Mymensingh	Bhaluka	20	18.1	

Mymensingh	Dhobaura	20		
Mymensingh	Fulbaria	19		
Mymensingh	Gaffargaon	17		
Mymensingh	Gauripur	15		
Mymensingh	Haluaghat	17		
Mymensingh	Ishwarganj	20		
Mymensingh	Mymensingh Sadar	18		
Mymensingh	Muktagachha	19		
Mymensingh	Nandail	19		
Mymensingh	Phulpur	16		
Mymensingh	Trishal	17		
Narayanganj	Araihazar	14	19	
Narayanganj	Sonargaon	17		
Narayanganj	Bandar	19		
Narayanganj	Narayanganj Sadar	29		
Narayanganj	Rupganj	16		
Narsingdi	Belabo	20	17.3	
Narsingdi	Manohardi	19		
Narsingdi	Narsingdi Sadar	17		
Narsingdi	Palash	13		
Narsingdi	Roypura	18		
Narsingdi	Shibpur	17		
Netrakona	Atpara	21	20.6	
Netrakona	Barhatta	20		
Netrakona	Durgapur	25		
Netrakona	Khaliajuri	22		
Netrakona	Kalmakanda	20		
Netrakona	Kendua	19		
Netrakona	Madan	19		
Netrakona	Mohanganj	21		
Netrakona	Netrokona Sadar	19		
Netrakona	Purbadhala	20		
Rajbari	Balia Kandi	16	18	
Rajbari	Goalandaghat	16		
Rajbari	Kalukhali	18		
Rajbari	Pangsha	18		
Rajbari	Rajbari Sadar	22		
Shariatpur	Bhedarganj	21	18.8	
Shariatpur	Damudya	13		
Shariatpur	Gosairhat	20		
Shariatpur	Naria	17		
Shariatpur	Shariatpur Sadar	21		
Shariatpur	Zanjira	21		
Sherpur	Jhenaigati	18	18.8	
Sherpur	Nakla	20		
Sherpur	Nalitabari	17		

Sherpur	Sherpur Sadar	20		
Sherpur	Sreebardi	18		
Tangail	Basail	21	19.4	
Tangail	Bhuapur	18		
Tangail	Delduar	17		
Tangail	Dhanbari	20		
Tangail	Ghatail	20		
Tangail	Gopalpur	19		
Tangail	Kalihati	18		
Tangail	Madhupur	19		
Tangail	Mirzapur	19		
Tangail	Nagarpur	22		
Tangail	Sakhipur	20		
Tangail	Tangail Sadar	20		
Bagerhat	Bagerhat Sadar	18	19.1	
Bagerhat	Chitalmari	16		
Bagerhat	Fakirhat	18		
Bagerhat	Kachua	18		
Bagerhat	Mollahat	20		
Bagerhat	Mongla	21		
Bagerhat	Morrelganj	22		
Bagerhat	Rampal	19		
Bagerhat	Sarankhola	20		
Chuadanga	Alamdanga	19	19.3	
Chuadanga	Chuadanga Sadar	20		
Chuadanga	Damurhuda	17		
Chuadanga	Jiban Nagar	21		
Jessore	Abhaynagar	18	18.5	
Jessore	Bagher Para	20		
Jessore	Chaugachha	21		
Jessore	Jhikargachha	18		
Jessore	Keshabpur	16		
Jessore	Kotwali	19		
Jessore	Manirampur	19		
Jessore	Sharsha	17		
Jhenaidah	Harinakunda	20	19.7	
Jhenaidah	Jhenaidah Sadar	20		
Jhenaidah	Kaliganj	21		
Jhenaidah	Kotchandpur	18		
Jhenaidah	Maheshpur	19		
Jhenaidah	Shailkupa	20		
Khulna	Batiaghata	19	16.1	
Khulna	Dacope	19		
Khulna	Daulatpur	6		
Khulna	Dumuria	19		
Khulna	Dighalia	14		

Khulna	Khan Jahan Ali	6		
Khulna	Khulna Sadar	23		
Khulna	Koyra	19		
Khulna	Paikgachha	21		
Khulna	Phultala	16		
Khulna	Rupsa	19		
Khulna	Sonadanga	7		
Khulna	Terokhada	21		
Kushtia	Bheramara	17	17.2	
Kushtia	Daulatpur	19		
Kushtia	Khoksa	12		
Kushtia	Kumarkhali	18		
Kushtia	Kushtia Sadar	19		
Kushtia	Mirpur	18		
Magura	Magura Sadar	19	19.3	
Magura	Mohammadpur	19		
Magura	Shalikha	21		
Magura	Sreepur	18		
Meherpur	Gangni	20	19.3	
Meherpur	Mujib Nagar	16		
Meherpur	Meherpur Sadar	22		
Narail	Kalia	22	20.7	
Narail	Lohagara	18		
Narail	Narail Sadar	22		
Satkhira	Assasuni	18	18.7	
Satkhira	Debhata	20		
Satkhira	Kalaroa	20		
Satkhira	Kaliganj	17		
Satkhira	Satkhira Sadar	17		
Satkhira	Shyamnagar	19		
Satkhira	Tala	20		
Bogra	Adamdighi	16	17.3	
Bogra	Bogra Sadar	15		
Bogra	Dhunat	20		
Bogra	Dhupchanchia	15		
Bogra	Gabtali	15		
Bogra	Kahaloo	17		
Bogra	Nandigram	21		
Bogra	Sariakandi	21		
Bogra	Shajahanpur	15		
Bogra	Sherpur	17		
Bogra	Shibganj	20		
Bogra	Sonatola	16		
Joypurhat	Akkelpur	21	18.4	
Joypurhat	Joypurhat Sadar	18		
Joypurhat	Kalai	20		

Joypurhat	Khetlal	14		
Joypurhat	Panchbibi	19		
Naogaon	Atrai	19	19	
Naogaon	Badalgachhi	21		
Naogaon	Dhamoirhat	18		
Naogaon	Manda	17		
Naogaon	Mahadebpur	18		
Naogaon	Naogaon Sadar	17		
Naogaon	Niamatpur	19		
Naogaon	Patnitala	20		
Naogaon	Porsha	19		
Naogaon	Raninagar	20		
Naogaon	Sapahar	21		
Natore	Bagati Para	17		
Natore	Baraigram	17	18.2	
Natore	Gurudaspur	22		
Natore	Lalpur	17		
Natore	Natore Sadar	17		
Natore	Singra	19		
Nawabganj	Bholahat	18	19.2	
Nawabganj	Gomastapur	20		
Nawabganj	Nachole	18		
Nawabganj	Nawabganj Sadar	20		
Nawabganj	Shibganj	20		
Pabna	Atgharia	22	19	
Pabna	Bera	18		
Pabna	Bhangura	18		
Pabna	Chatmohar	18		
Pabna	Faridpur	19		
Pabna	Ishwardi	18		
Pabna	Pabna Sadar	18		
Pabna	Santhia	20		
Pabna	Sujanagar	20		
Rajshahi	Bagha	23	17.7	
Rajshahi	Baghmara	17		
Rajshahi	Boalia	14		
Rajshahi	Charghat	23		
Rajshahi	Durgapur	17		
Rajshahi	Godagari	18		
Rajshahi	Mohanpur	18		
Rajshahi	Paba	20		
Rajshahi	Puthia	20		
Rajshahi	Rajpara	6		
Rajshahi	Tanore	19		
Sirajganj	Belkuchi	18	20.4	
Sirajganj	Chauhali	23		

Sirajganj	Kamarkhanda	22		
Sirajganj	Kazipur	23		
Sirajganj	Royganj	19		
Sirajganj	Shahjadpur	21		
Sirajganj	Sirajganj Sadar	20		
Sirajganj	Tarash	16		
Sirajganj	Ullah Para	22		
Dinajpur	Birampur	14	18	
Dinajpur	Birganj	19		
Dinajpur	Biral	21		
Dinajpur	Bochaganj	21		
Dinajpur	Chirirbandar	16		
Dinajpur	Fulbari	18		
Dinajpur	Ghoraghat	23		
Dinajpur	Hakimpur	17		
Dinajpur	Kaharole	15		
Dinajpur	Khansama	18		
Dinajpur	Dinajpur Sadar	18		
Dinajpur	Nawabganj	17		
Dinajpur	Parbatipur	18		
Gaibandha	Fulchhari	21	19.4	
Gaibandha	Gaibandha Sadar	17		
Gaibandha	Gobindaganj	21		
Gaibandha	Palashbari	18		
Gaibandha	Sadullapur	21		
Gaibandha	Saghatta	20		
Gaibandha	Sundarganj	18		
Kurigram	Bhurungamari	18	21	
Kurigram	Char Rajibpur	23		
Kurigram	Chilmari	23		
Kurigram	Phulbari	25		
Kurigram	Kurigram Sadar	18		
Kurigram	Nageshwari	20		
Kurigram	Rajarhat	22		
Kurigram	Raumari	18		
Kurigram	Ulipur	22		
Lalmonirhat	Aditmari	20	18.6	
Lalmonirhat	Hatibandha	21		
Lalmonirhat	Kaliganj	19		
Lalmonirhat	Lalmonirhat Sadar	15		
Lalmonirhat	Patgram	18		
Nilphamari	Dimla	18	19	
Nilphamari	Domar	16		
Nilphamari	Jaldhaka	21		
Nilphamari	Kishoreganj	18		
Nilphamari	Nilphamari Sadar	19		

Nilphamari	Saidpur	22		
Panchagarh	Atwari	17	17.4	
Panchagarh	Boda	16		
Panchagarh	Debiganj	18		
Panchagarh	Panchagarh Sadar	20		
Panchagarh	Tentulia	16		
Rangpur	Badarganj	16	18	
Rangpur	Gangachara	18		
Rangpur	Kaunia	21		
Rangpur	Rangpur Sadar	20		
Rangpur	Mitha Pukur	18		
Rangpur	Pirgachha	16		
Rangpur	Pirganj	18		
Rangpur	Taraganj	17		
Thakurgaon	Baliadangi	19	19	
Thakurgaon	Haripur	17		
Thakurgaon	Pirganj	20		
Thakurgaon	Ranisankail	21		
Thakurgaon	Thakurgaon Sadar	18		
Habiganj	Ajmiriganj	22	19.8	
Habiganj	Bahubal	19		
Habiganj	Baniachong	21		
Habiganj	Chunarughat	21		
Habiganj	Habiganj Sadar	20		
Habiganj	Lakhai	19		
Habiganj	Madhabpur	17		
Habiganj	Nabiganj	19		
Maulvibazar	Barlekha	19	19.6	
Maulvibazar	Juri	17		
Maulvibazar	Kamalganj	21		
Maulvibazar	Kulaura	20		
Maulvibazar	Maulvi Bazar Sadar	20		
Maulvibazar	Rajnagar	20		
Maulvibazar	Sreemangal	20		
Sunamganj	Bishwambarpur	17	20.4	
Sunamganj	Chhatak	21		
Sunamganj	Dakshin Sunamganj	22		
Sunamganj	Derai	21		
Sunamganj	Dharampasha	22		
Sunamganj	Dowarabazar	19		
Sunamganj	Jagannathpur	17		
Sunamganj	Jamalganj	22		
Sunamganj	Sulla	22		
Sunamganj	Sunamganj Sadar	18		
Sunamganj	Tahirpur	20		
Sylhet	Balaganj	20	19.5	

Sylhet	Beani Bazar	21		
Sylhet	Bishwanath	20		
Sylhet	Companiganj	17		
Sylhet	Dakshin Surma	20		
Sylhet	Fenchuganj	18		
Sylhet	Golabganj	22		
Sylhet	Gowainghat	23		
Sylhet	Jaintiapur	16		
Sylhet	Kanaighat	19		
Sylhet	Sylhet Sadar	18		
Sylhet	Zakiganj	20		
			National Average prediction value = 19	