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Socio-Economic Status Classification for Poverty Mitigation

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Abstract - The concept of satellite images available from various sources using image processing technique provides an insight to predict or determine the poverty at various levels based on certain features like roads, buildings, schools and other factors. In the present scenario we are making use of Convolutional Neural Networks (CNN) mainly used for image recognition and processing to predict the poverty at various levels. The efficiency and accuracy of the model depends upon the number of pre-processing steps employed, the number of datasets used, the type of welfare indicator targeted and the choice of AI model. Leveraging advanced algorithms together with the ample amount of geographic information which satellites capture offers an appropriate approach for delicate socio-economic indicator evaluation. Leveraging advanced algorithms together with the ample amount of geographic information which satellites capture offers an appropriate approach for delicate socio-economic indicator evaluation.

Key Words: *Convolutional neural networks, ReLU architecture, Gaussian Blur*

1. INTRODUCTION

Povertydetectionisaveryhardtaskandifitweretobedone by different agencies then each of them will be providing a different statistic altogether and a colossal amount of effort is put in just to estimate income statistics. When it comes to povertyalleviationordetection,peopleandworldagenciesare usually in a fix. Even though poverty is quite evident most of the time, for example it is very easy to judge which areas are moreaffluentand opulentthan others,therestill seems tobe a problem on paper. On paper some areas may have very high-income levels but the ground truth may be that the income inthat area may be distributed amongst a handful of people only. The current challenge in this domain is that agencies acrosstheworldwhopredictincomelevelstakeahugeamount of time to do the same.

2. OVERVIEW

2.1 RELATEDWORKS

Abitboland et al [1] delvesintothecorrelation between socioeconomic data and urban patterns inferred from aerialimagesusing CNNs,offering insightsinto deep learning's potential for urban planning and socioeconomic research. Aikenetal [2]exploremachinelearningandmobilephonedatato target populations for anti-poverty programs, showcasing innovative resource allocation methods. Karlan and Udry[3] highlight the integration of satellite and smartphone data for precise emergency response operations, enhancing efficiency in critical situations. Burke et al [4] focus on using satellite imagery to support sustainable development initiatives, providing crucial data for policy decisions and climate change mitigation. Engstrom and et al [5] employ high- resolutionsatelliteimagestoestimateeconomicwell-beingand address poverty, emphasizing the importance of data-driven methodologies for mapping and monitoring poverty solutions. Another study integrates high-resolution satellite imagery withCNNsforpovertyprediction,showcasingrobustpredictive power and model transferability across countries. The research by Liverpool University [7] contributes significantly to urbanpovertyassessmentusingmachinelearning,highlighting the effectiveness of advanced geospatial data analysis techniques.Furthermore,acomprehensivemethodologyfor identifyingslumsandpredictingpovertyratesinAccra and et al [8] underscorestheroleofmachinelearninganddataintegrationin poverty assessment and targeted interventions. Introducing the random forest algorithm [9] for poverty status prediction, the study compares its efficacy with traditional econometric models, showcasing superior predictive capability and feature selection effectiveness. Lastly, a random forest regression [10] model for poverty estimation in Bangladesh and Nepal emphasizes accessibility as a key determinant of poverty, despite challenges like multi collinearity. These studies collectively showcase the transformative potential of data-driven approaches and advanced technologies in addressing urban poverty and supporting sustainable development goals.

2.2 PROBLEMSTATEMENT

Thepersistentchallengeofpovertycontinuestoimpact communities worldwide, hindering socio-economic development and human well-being. Traditional methods of poverty assessment often lack the granularity and timeliness requiredforeffectiveinterventions. Inthiscontext,theproject aims to developanadvancedsystemforpovertyprediction using satellite imagery and machine learning techniques.

The problem statement revolves around classifying regionsbasedontheirpovertylevels.Thegoaloftheprojectis to provide fundraisers and policymakers with an efficient way to formulate policies aimed at reducing poverty levels. The proposed system aims to overcome the drawbacks of existing systems by analysing structured data and making predictions based on influential parameters. The solution we propose isto design a system that considers the most influential factors to categorize areas accurately, leading to a better mapping of poverty.Thisapproachmaximizebenefitsforpeoplebelowthe poverty line, thereby reducing poverty and increasing the overall wealth index.

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2.3 PROPOSED SOLUTION

The system introduces a method for region classification using a blend of Machine Learning and Deep Learning algorithms. It employs advanced techniques like Convolutional Neural Networks (CNNs) with specific functionalities like Input Layer, Conv2D (Convolutional Layer), MaxPooling2D, Flatten Layer, Dense Layer, Multi-Layer Perceptrons (MLPs), Activation Functions such as RectifiedLinearUnit(ReLU),CategoricalCross-EntropyLoss Function,andtheAdamOptimizer.Thesemodelsareharnessed to categorize regions into three distinct classes: developed, under-developed and developing regions, leveraging the available features for accurate poverty prediction.

2.4 METHODOLOGY

A. Data Collection and Preprocessing

The dataset used in this project is taken from the publicly available sources(Kaggle) and database related to socioeconomic indicators and poverty assessment.Images were selected to represent various scenarios and environments associatedwithdifferentstagesofdevelopment.Eachimageis manually labelled to indicate one of the following categories- developed, under-developed and developing regions.

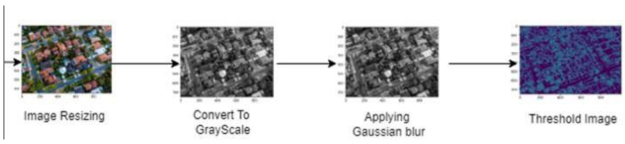


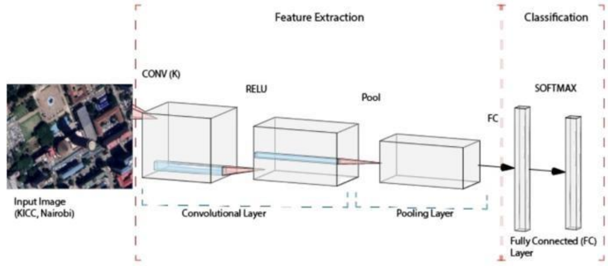
Fig.1ROCCurveofproposedmethod

Before training the model, we have made sure the images are all in the same format and improve their quality for easier categorization. RGB images were converted to grayscale to reduce computational complexity and focus on the important partsoftheimagesthathelpdeterminepovertylevels.Gaussian blurring was applied to reduce noise and smooth out irregularities in the images, thereby enhancing the clarity of importantfeatures.A thresholding technique wasemployedto segment theimages and highlight key regionsof interest. This step facilitated the extraction of relevant features related to poverty assessment. All images were resized to a fixed dimensionof50x50pixelstoensureuniformityandconsistency in the input data in dataset.

B. ModelArchitecture

The CNNdesign isused to accurately recognizeand sort out features related to poverty from the images we prepared earlier.Ithasspecificpartsthatareimportantforthistask.The model consists of multiple convolutional layers followed by batch normalization and Rectified Linear Unit (ReLU) activation functions. These layers were responsible for extractinghierarchicalfeaturesfromthe inputimages.These layers made sure to enhance the important features step by step. The model includes extra connections between certain layers, kind of like shortcuts. These shortcuts helped the trainingprocessandmadesurethatthemodelcouldlearnboth simple and complex features well without losing track. The output of the convolutional layers was flattened and passed through fully connected layers to perform classification. To avoid the model focusing too much on specific details and becoming too specialized, some neurons were randomly turnedoffduringtraining.Thelastlayerofthemodelwasset up to give the probability of each image belonging to one of three poverty categories.

Fig.2 Architectureofconvolutionalneuralnetwork

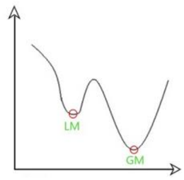


C. ModelTraining

The model was trained using the Adam optimizer with a learning rate of 0.001. The categorical cross-entropy loss function was chosen to measure the disparity between predicted and actual class probabilities during training, we usedamethodcalledAdamoptimizerwithaspecificlearning ratetoadjustthemodel'sparameters.Wemeasuredhowwell themodelwasdoingusingamethodcalledcategoricalcross-entropy loss. Training was done in batches, with each batch containing32images,andwerepeatedthetrainingprocess10 times. We also checked how well the model was doing on a separatesetofimagestomakesureitwasn'tjustmemorizing thetrainingdata.Wesavedthebestversionofthemodelbased on how well it performed on this separate set.
Taking the formulas used in the above two methods,

$$m_t=\beta_1 m_{t-1}+(1-\beta_1)\left[\frac{\delta L}{\delta w_t}\right] \quad - 1$$

$$v_t=\beta_2 v_{t-1}+(1-\beta_2)\left[\frac{\delta L}{\delta w_t}\right] \quad - 2$$



GM-global minimum
LM-Local minimum

Fig.3GraphtodemonstrateAdamoptimizer

Adam Optimizer inherits the strengths or the positiveattributes of the above two methods and builds upon them to give a more optimized gradient descent. Here, we control the rate of gradient descent in such a way that there is minimum oscillation when it reaches the global minimum while taking big enough steps (step-size) so as to pass the local minima hurdles along the way. Hence, combining the features of the above methods to reach the global minimum efficiently.

3. RESULTS

Following model training, comprehensive evaluation was performed to assess the model's performance in classifying poverty levels. The evaluation comprised both quantitative and qualitative analyses:

Quantitativeevaluationinvolvedcomputingmetricssuch as test loss and accuracy to quantify the model's classification performance. We looked at metrics like loss and accuracy to measure how good the model was at classifyingthesenewimages.Thishelpedusunderstandhow wellthemodelcouldworkinreal-worldsituationswithnew data. **C**onfusionmatrixwasgeneratedtoprovideinsightsinto the model's classification behavior across different poverty categories.It allowed for theanalysisof truepositive,false positive, true negative, and false negative predictions, thereby enabling a detailed assessment of classification errors.

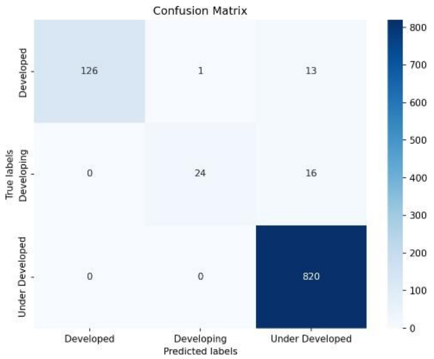


Fig.4 Confusion Matrix of proposed method

Developed Class: 126 instances were correctly predicted as Developed (True Positive for Developed). 1 instance was incorrectly predicted as Developing.13 instances were incorrectly predicted as Under Developed. Developing Class: 24 instances were incorrectly predicted as Developed.16 instances were correctly predicted as Developing (True Positive for Developing). Under Developed Class: All 820 instances were correctly predicted as Under Developed (True Positive for Under Developed).

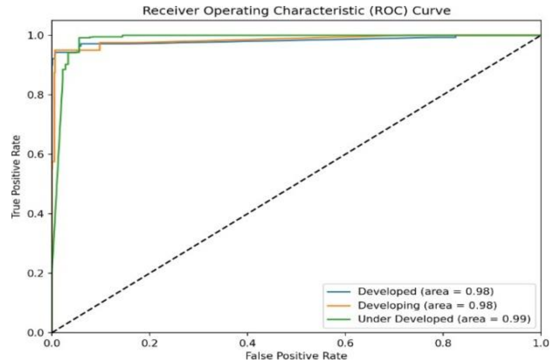
ROCcurveswereconstructedtovisualizethemodel's ability todiscriminatebetween poverty categories.Wemade some graphs called ROC curves to see how well the model couldtellthedifferencebetweendifferentlevelsofpoverty. Theareaunderthesecurves(AUC)gaveusasinglenumber to summarize how good the model was at distinguishing between the poverty levels. In the context of multi-class classification, as in this case with three poverty categories, ROC curves can be generated for each class individually using a one-vs-all approach.

The true positive rate (TPR), also known as sensitivity, represents the proportion of positive instances (correctly classified as positive) that are correctly identified by the model. It is calculated as: TPR = TP/TP+FN (TP is the number of true positives FN is the number of false negatives). False Positive Rate (Specificity): The false positiverate(FPR),alsoknownasspecificity,representsthe proportionofnegativeinstances(incorrectlyclassifiedaspositive)thatareincorrectlyidentifiedaspositivebythe model. It is calculated as: FPR = FP/FP+TN.

TheAreaUndertheCurve(AUC)ROC isascalarvalue that quantifies the overall performance of the model in discriminatingbetweenclasses.Itrepresentstheprobability thatthemodelwillrankarandomlychosenpositiveinstance higher than a randomly chosen negative instance.

To evaluate the proposed Convolutional Neural Network (CNN) model for poverty detection, various performance metrics were used to gauge the model's effectiveness. The results are presented in terms of Area Under the Curve (AUC) ROC, confusion matrix, and classification report, offering a comprehensive view of the model's performance across different categories. The Area Under the Curve (AUC) ROC, asshowninFig.5,isakeyindicatorofthemodel'scapacityto distinguish between different classes of development. For the Developedcategory,theAUCscorewas0.98,indicatinggood accuracy, while the Developing category achieved an AUC of 0.98, showing equal performance as previous. The Under Developed category had an AUC of 0.99 which shows better performance. The Normal category, with an AUC of 1.00, indicated perfect separation from other classes.

Fig.5 ROC Curve of proposed method



To streamline the detection process and improve the model's ability to recognize and categorize different levels of development, the classes were consolidated into three broader categories: developed area, developing area and under developed area.

Fig.6UnderDevelopedArea

Fig.7 Developing Area

Fig.8DevelopedArea

Table.1 Comparison of outcomes with existing methods.

Sl. No.	Previous work by	Method	Accuracy
1	Patrick et al.	MobileNetV2	98%
2	Our Study	CNN	94%

4. CONCLUSION

The proposed solution employs a blend of Machine Learning and Deep Learning algorithms, particularly CNNs, to categorize regions into developed, under-developed, and developing areas based on poverty levels. The model architecture includes multiple convolutional layers followed by batch normalization and ReLU activation functions for feature extraction and classification. Training the model using the Adam optimizer with a specific learning rate and categorical cross-entropy loss function ensures optimal parameter adjustment and measurement of classification performance.

Comprehensive evaluation metrics such as test loss, accuracy, confusion matrix, and ROC curves provide insights into the model's classification behavior and its ability to discriminate between poverty categories. The results demonstrate the effectiveness of the CNN model in accurately predicting measures of poverty, with high AUC scores indicating good accuracy across different development categories.

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