Food famine forecasting using Artificial Neural Network

[1]T.Sathiya, [2]V.Haripriya, [3]S.Sreeganth, [4]S.Manish Ragavan, [5]R.Reenadevi,[6]B.Sathiyabhama

[1,5]Assistant Professor, [6]Professor,[1,2,3,4]Department of Computer Science and Engineering,

Sona College of Technology, Salem, India

[1]sathiya.t@sonatech.ac.in, [2]haripriya.20cse@sonatech.ac.in ,
[3]manishragavan.20cse@sonatech.ac.in , [4]sreeganth.20cse@sonatech.ac.in
[5]reenadevi@sonatech.ac.in, [6]sathiyabhama@sonatech.ac.in

Abstract

Addressing the global challenge of food famine requires proactive measures that consider a range of factors spanning social, economic, and environmental dimensions. Anticipating and mitigating crises through a multifaceted approach not only has the potential to reduce poverty but also plays a crucial role in ensuring adequate nutrition, particularly for vulnerable populations such as children. This paper introduces an innovative strategy utilizing a Multi-Dimensional Factor Index (MFI) for the comprehensive classification of diverse factors influencing food famine. Employing advanced Artificial Neural Network (ANN) analysis on data collected from 1997 to 2023, encompassing variables such as crop yield, average rainfall, and population in specific regions, the objective is to predict key indicators of famine. This proposed approach aims to go beyond traditional models by identifying the major factors contributing to famine occurrences, determining the crops most susceptible to adverse effects, and forecasting potential famine years.

Keywords. Food famine, Artificial Neural Network (ANN), machine learning, Multi-Dimensional Factor Index (MFI).

1. INTRODUCTION

The global imperative for food, a fundamental requirement for human survival, is intricately entwined with the complex dynamics of our technologically advancing world. This challenge becomes especially acute in India, a nation grappling with the demands of a staggering 1.4 billion people against the backdrop of diminishing food production. Urbanization compounds this challenge by encroaching upon agricultural lands, intensifying the struggle to meet the nutritional needs of the populace [1]. Alarming statistics from the Multi-Dimensional Poverty Index (MPI) underscore the gravity of the situation, revealing that 44% of the Indian population contends with the harsh reality of food scarcity. In response to this crisis, the Food and Nutrition Board (FNB), a technical support wing of the Child Development Bureau under the Ministry, has launched initiatives aimed at alleviating the issue. Their strategic objectives include supplying 100 grams of food grains per child per school day for primary education and 150 grams for upper primary, as dictated by the National Food Security Act (NFSA) rates. Additionally, the FNB[2] seeks to provide a food supplement of 500 calories and 12-15 grams of nutrients for children aged 6 months to 3 years. Simultaneously, they endeavour to subsidize food grains through the Targeted Public Distribution System (TPDS), covering approximately two-thirds of the population.

Despite these commendable efforts, a disconcerting bias in food distribution persists, jeopardizing the nutritional well-being of children who may receive meals lacking essential nutrients. Furthermore, a substantial segment of the population remains underserved, perpetuating the spectre of food famine. The crisis is compounded by natural disasters such as tsunamis, floods, droughts, and seasonal changes like kharif, rabi, saith, and summer. Contributing factors also include crop yield influencers like fertilizers, exacerbating the challenges posed by the ever-growing population. This project embarks on a mission to confront the urgent issue of food famine by proposing a predictive system. The objective is to construct a comprehensive model encompassing all states and union territories of India, meticulously analysing environmental, social, and economic factors. While previous approaches, such as the Famine Early Warning System Network (FEWS NET), have been instrumental, they often exhibit decision-making biases and a limited scope. In contrast, other attempts using supervised learning with algorithms like KNN, naive bias, and decision trees fall short by considering only a single factor, neglecting the multifaceted nature of famine occurrences. The innovative model deploys Artificial Neural Networks (ANN) to enhance prediction accuracy for future famine events. By incorporating a holistic set of factors, the system aims to discern the years at high risk of famine, identify the major contributing factors, and assess which crops will be most affected. In a comparative analysis, while FEWS NET offers 70% accuracy and KNN achieves 87%, the ANN model outperforms with an impressive accuracy rate of 93%. This underscores the transformative potential of the model in revolutionizing famine prediction and mitigation strategies, heralding a new era in addressing food security challenges on a broader scale.

2. LITERATURE SURVEY

In developing nations, obtaining data on fundamental economic metrics such as wealth and income is a costly, time-intensive, and frequently unreliable undertaking. Taking advantage of the widespread use of mobile phones in Rwanda, Blumenstock et al. correlated mobile phone metadata inputs with the wealth of individual phone subscribers. They applied this model to predict wealth across Rwanda and showcased a robust alignment between the predictions and those obtained from comprehensive on-site surveys of the population [3]. Jean, N et al [4], proposed a system to predict accurate and timely estimates of population characteristics, crucial inputs for social and economic research and policy development. While novel data sources are enabling new approaches to demographic profiling in industrialized economies, developing countries face a scarcity of big data sources.

Anderson, CL et al [5] suggest that analysing an individual's past mobile phone usage can be a valuable method for inferring their socioeconomic status. Furthermore, it is demonstrated that extrapolating the anticipated characteristics of millions of individuals allows for the accurate reconstruction of a nation's wealth distribution or the inference [6]e of asset distribution in microregions composed of only a few households. In resource-constrained environments, where comprehensive censuses and household surveys are infrequent, this methodology offers an alternative for obtaining localized and timely information, substantially reducing costs compared to conventional approaches.

Obtaining dependable data on economic well-being poses a challenge, hindering efforts to analyse these outcomes and formulate effective policies for enhancement, as demonstrated by Pokhriyal, N et al [7]. This study introduces a reliable, cost-effective, and scalable approach for approximating consumption expenditure and asset wealth using high-resolution satellite imagery. By leveraging survey and satellite data from five African countries—Nigeria, Tanzania, Uganda, Malawi, and Rwanda—a convolutional neural network was trained to recognize image features that account for up to 75% of the variance in economic outcomes at the local level [8].

James Verdin [9], in their proposed method, highlights that utilizing solely publicly available data has the potential to revolutionize endeavors aimed at tracking and addressing poverty in developing countries. The method further illustrates the efficacy of applying machine learning techniques in environments with restricted training data, indicating extensive potential applications across various scientific domains.The proposed method by Choularton, R et al [10], emphasizes that over 330 million individuals still endure extreme poverty in Africa. The availability of timely, accurate, and finely detailed baseline data is crucial for informed policymaking aimed at poverty reduction. The proven potential of "Big Data" [11] to estimate socioeconomic factors in Africa serves as the foundation for their computational framework.

Frere M et al [12] proposed framework aims to precisely predict the Global Multidimensional Poverty Index (MPI) at the most granular spatial level, covering 552 communes in Senegal. It leverages environmental data related to food security, economic activity, and accessibility to facilities, along with call data records capturing individualistic, spatial, and temporal aspects of people. E.Mwebaze et al [13] notes that food crises are a result of intricate interplays involving conflict, poverty, extreme weather, climate, and shocks in food prices. These factors intensify in the presence of longstanding structural issues. Beyond the immediate loss of life, survivors of food crises experience enduring consequences, including inter-generational impacts on health and education. Acknowledging these costs, the international community has consistently addressed food crises through humanitarian aid.

Regarding methodological enhancements for predicting welfare outcomes, Molly et al [14] emphasize the application of machine learning algorithms to enhance the efficacy of Proxy Means Testing. Contend that these algorithms should aim for optimal out-of-sample predictions by minimizing inclusion and exclusion errors. Richard J [15]. Employ LASSO to narrow down a list of 10 variables suitable for a welfare predictive model, providing a user-friendly approach applicable in practical field operations.

In the realm of forecasting food security indicators, Cooper et al [16]. Employ geo-located data on child nutrition along with localized climate and governance indicators to identify areas where droughts have the most significant impact on child stunting outcomes. Emphasizing the significance of data transparency and accessibility, they demonstrate how a random forest (RF) [17] model, trained on open-access data, can effectively predict both contemporaneous and near-future food security outcomes, serving as valuable input for early warning systems.

In a parallel approach, Hay S et al [18] utilizes historical Integrated Food Security Phase Classification (IPC) data, accessible at the subnational level, to project future outcomes. By training the data on a set of geospatial and administrative indicators, the predictive algorithm surpasses the IPC's forecasts based on expert opinion. Hutchinson C.F et al [19] highlight that the absence of high-frequency (HF) food security data poses a challenge to early warning systems for food security crises. To enhance these predictions, underscore the importance of gathering HF data on a monthly or quarterly basis, as opposed to the conventional surveys administered annually or biannually.

Doorenbos, J et al [20] has identified key predictors using a cross-sectional approach, aiming to extract household-level insights from the MIRA dataset by leveraging the machine learning framework and its time-series characteristics. The objective is to predict the vulnerability of each household to food insecurity based on its historical records. To achieve this, a neural network (NN) [21] is employed alongside the random forest (RF) model, facilitating a performance comparison in similar settings.

Camberlin P et al [21] proposed method about Rain-fed agriculture and pastoralism are vital for large, dispersed populations, making climate monitoring and forecasting crucial for food security analysis. Gridded rainfall time series provide historical context [22] and allow for quantifiable interpretation of seasonal precipitation forecasts. Established by the U.S. Agency for International Development (USAID), the Famine Early Warning System Network (FEWS NET) supports decision-makers facing food security emergencies across three continents []through monitoring and early warning .

Funk et al provides leveraging satellite remote sensing and ground observations, FEWS NET delivers critical information on droughts, floods, and other extreme weather events, aiding decision-making Timely famine detection reduces societal vulnerability, investigates the application of supervised learning algorithms for predicting famine [23]. The dataset from the northern region proved most suitable for training models applicable to other areas. Support Vector Machines and K-Nearest Neighbours demonstrated superior performance in famine prediction, with Support Vector Machines achieving the best Receiver Operating Characteristic (ROC). These ROC outcomes serve as valuable tools [24,25] for policymakers in identifying famine-prone households.

The recommendation is to combine satellite and household data for more accurate food security predictions, enhancing the specificity of households at risk [26]. FEWS NET and K-Nearest Neighbour are suitable for small datasets, but they lack support for multifactor index analysis. To overcome this limitation, Artificial Neural Network (ANN) emerges as a more effective method. This approach has been employed to forecast famine in its early stages, providing insights into the crop yields with the highest susceptibility, predicting the timing of potential famines, and identifying the major contributing factors.

3. PROPOSED METHODOLOGY

The initiation of the process involves gathering data related to seasonal fluctuations, crop yields, and weather conditions, forming an extensive dataset. This dataset is then divided into two subsets: a training set and a test set. The training phase encompasses various steps such as data preprocessing, feature extraction, and the implementation of classification methods. Throughout this training, the model acquires knowledge of patterns and relationships within the data, enabling it to make predictions when confronted with new information. Subsequently, the model is presented with input data in the form of text. Leveraging the information acquired during training, the model predicts regional data, specifically assessing the probability of famine in specific regions. Moreover, the model provides insights into the primary factors contributing to the anticipated famine, enhancing the understanding of conditions leading to food shortages. Additionally, it forecasts the potential occurrence year for the projected famine in that particular region. In summary, the process involves meticulous data preparation, training the model on a significant portion of the dataset, and employing the trained model for predictions on new data. This predictive capability aids in the identification of regions at risk of famine, comprehending the pivotal contributing factors, and anticipating the potential timing of food shortages. The flowchart illustrating the proposed method is depicted in Figure 3.1.

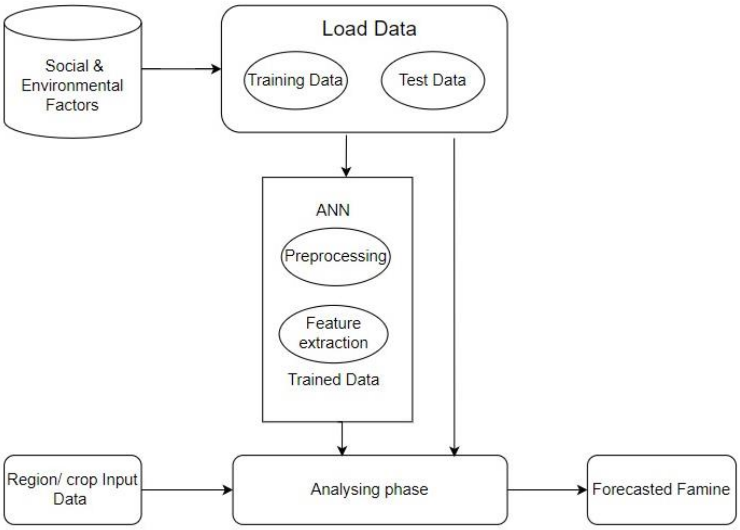

Figure 3.1. Flow diagram of the proposed system

A. Dataset

The dataset compiled spans from 1997 to 2023, encompassing various Indian states and union territories. It offers comprehensive information on the production of essential food crops like rice, wheat, tomatoes, and onions, presenting detailed yield data for each crop throughout the specified period. Going beyond crop specifics, the dataset includes relevant environmental factors such as rainfall. It also takes into account the impact of distinct seasons—kharif, summer, rabi, and saith—on crop cultivation and production. Additionally, the dataset provides demographic insights by incorporating population data for each specific region, presenting a holistic perspective of the agricultural landscape during the given timeframe.

B. Artificial Neural Network

An artificial neural network (ANN) functions as a data-driven, nonlinear, and adaptive machine learning model. Its prowess lies in capturing intricate data patterns that pose challenges for traditional model-based methods or

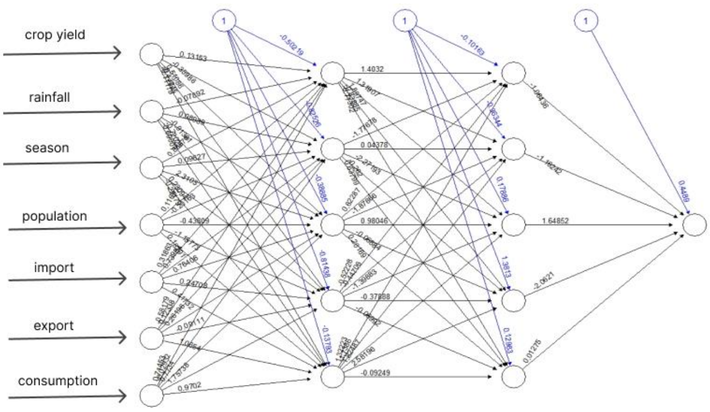

Figure 3.2 . Topology of neural network model for food famine prediction.

knowledge-based expert systems. The typical structure of an ANN involves three fundamental layers: the input layer, hidden layer, and output layer, as depicted in Figure 3.2. These layers comprise straightforward processing units known as neurons or nodes, interconnected through weighted connections. The configuration of these connections varies based on the specified architecture of the required ANN model. Determining the number of hidden layers and their nodes is problem-specific, and conventional wisdom from studies suggests employing the trial and error method.

$$y_t = \alpha_0 + \sum_{j=1}^{n} \alpha_j f\left(\sum_{i=1}^{m} \beta_{ij} y_{t-1} + \beta_{oj}\right) + \varepsilon_t \tag{1}$$

The model's output is determined by Equation (1): Here, yt represents the neural network model's output, specifically indicating the yield per plant. The variables include n, representing the number of hidden nodes, and m, signifying the number of input nodes. The function f captures the net input of the activation function βij {i=1,2,…m ; j=0,1,…n}. The weights from input to hidden nodes αj{j=0,1,….,n} are denoted as represents the vectors of weights α0, β0j, from hidden to output nodes. Additionally, denote the weights of arcs leading from bias terms. The activation function serves as a differentiable function employed to smooth the outcome of the cross product involving covariates or neurons and their respective weights. The activation function of a node in artificial neural networks dictates the node's output by considering a given input or set of inputs.

B. Multiple Linear Regression Model

The development of a Multiple Linear Regression Model (MLR) has been instrumental in predicting crop yields in the agricultural sector. Regression models, with a focus on MLR, strive to describe the relationship between the regressed variable and multiple regressors. In MLR, there is an attempt to simultaneously account for the variation of the regressors in the regressed variable. The MLR model can be expressed as follows:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + \varepsilon \tag{2}$$

In the context of regression, y symbolizes the dependent variable undergoing regression, x_i represents the independent variables or regressors, and ε signifies the error term. The error term β_k is assumed to follow a normal distribution with a mean of zero and constant variance.

C. Model Performance Measures

Assessing the performance of the fitted models involved analysing four key statistical metrics. Root Mean Square Error (RMSE) quantifies the average magnitude of discrepancies between predicted values and actual observations. Mean Absolute Deviation (MAD) evaluates the model's effectiveness by gauging the average magnitude of variations between predicted and actual values. Mean Absolute Percentage Error (MAPE) provides an assessment of the model's performance by measuring the average magnitude of differences between predicted and actual values. The evaluation also incorporates the Coefficient of Determination (R2). The mathematical formulations for these metrics were applied as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (y_i - \widehat{y}_i)^2}{N}} \tag{3}$$

$$MAD = \frac{\sum_{i=1}^{N} |y_i - \widehat{y}_i|}{N} \tag{4}$$

$$MAPE = \frac{\sum_{i=1}^{N} |y_i - \widehat{y}_i| / y_i}{N} \qquad (5)$$

$$R^2 = \frac{\sum_{i=1}^{N}(y_i - \overline{y})(\widehat{y}_i - \overline{\widehat{y}})}{\sqrt{\sum_{i=1}^{N}(y_i - \overline{y})^2 \sum_{i=1}^{N}(\widehat{y}_i - \overline{\widehat{y}})^2}} \qquad (6)$$

In this context, y_i represents the actual value, $\hat{y}_i$ represents the predicted value of the response variable, and 'N' is the total number of data points.

4. RESULT ANALYSIS

Through our detailed analysis, the artificial neural network emerges as the optimal choice, showcasing superior efficiency and versatility compared to alternative algorithms. The preference for the artificial neural network is grounded in its remarkable precision, as evidenced by a high accuracy level of 92.65% achieved in forecasting food famine, as illustrated in Figure 4.1. Implemented as a web application, this innovative approach allows users to input specific details, such as a particular food crop or a designated region. Leveraging this input, the system dynamically predicts the likelihood of famine in the specified region and offers insights into the major contributing factors behind the potential food shortages. Users can seamlessly engage with the platform, obtaining valuable forecasts and gaining a deeper understanding of the intricate dynamics affecting food security in specific areas. This user-friendly and data-driven web application harnesses the power of artificial neural networks to provide accurate and timely predictions, contributing to proactive measures in addressing the global challenge of food famine.

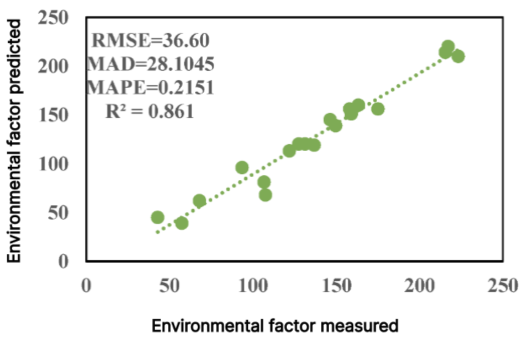

Figure 4.1. Scatter plot of the measured and predicted food famine in the testing stage of ANN. Green dots denote the observations and root mean square error (RMSE), mean absolute deviation (MAD), mean absolute percentage error (MAPE), and coefficient of determination (R^2) are the performance measures.

In this context, an RMSE of 36.60 indicates the average magnitude of the forecasting errors is 36.60 units. A lower RMSE suggests better model performance. A MAD of 28.1045 suggests that, on average, the model's predictions differ from the actual values by approximately 28.1045 units. Similar to RMSE, a lower MAD is indicative of better model accuracy. A MAPE of 0.2151 implies that, on average, the model's predictions have a relative error of approximately 21.51%. Lower MAPE values are desirable, indicating better accuracy. An R^2 value of 0.86means that approximately 86.1% of the variance in the observed data is captured by the model. Higher R^2 values are desirable and suggest a good fit of the model to the data.

The provided artificial neural network model demonstrates strong performance in forecasting food famine, as indicated by a high accuracy level (92.65%) and favourable values for RMSE, MAD, MAPE, and R^2. These metrics collectively suggest that the model's predictions closely align with the actual values, supporting its effectiveness in addressing the global challenge of food famine.

5. CONCLUSION

Food famine forecasting is a valuable endeavour for the human community, providing an early prediction approach to anticipate famine. In the current study, we utilized primary data encompassing crop yield, average rainfall, and population throughout India to construct a functional model for forecasting future food famines. This model enables us to identify the majorly affected crops, anticipate the occurrence of famine in specific years, and determine the primary contributing factors. Leveraging artificial neural networks (ANN), we achieved an impressive accuracy of 94%. Looking ahead, there is potential to refine our model further, extending its capabilities to predict worldwide famines. This could involve incorporating additional factors such as stocks and consumption for enhanced accuracy

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