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Continuous Learning for Food Recognition Using a Class-Increasing Extreme and Online Clustering Approach

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***Abstract*— The tendency of an artificial neural network to suddenly and catastrophically lose preliminarily learned information upon acquiring new information is known as disastrous hindrance, occasionally known as disastrous forgetting. The unique unrestricted ongoing learning framework proposed in the current research makes use of Relief F for point selection, transfer literacy on deep models for point birth, and a special adaptive reduced class incremental kernel extreme literacy machine (ARCIKELM) for framing. By classifying and ordering the recovered traits, Relief F lessens computational complexity. To help disastrous forgetting, the innovative ARCIKELM classifier stoutly modifies network armature. When fresh samples of the current class are entered, it solves sphere adaptation issues. Results reveal that the suggested frame earnings new knowledge. The system was further expanded to show the name, nation, and factors of the item also it indicates if the dish is adipose or healthy.**

***Index Terms*— Artificial neural network, disastrous, open-concluded nonstop literacy, and ARCIKELM.**

I. INTRODUCTION

New classes are continuously being added to the open-ended nonstop filmland of instruction. Open- ended ongoing literacy includes two different kinds of incremental literacy that are pivotal. 1) Data iterative literacy 2) Incremental literacy in classes. The data set structure is changing, and new topics that are relevant emerge from time to time. This highlights the importance of open-ended continuous literacy in a variety of real-world identification tasks, like food recognition. Both of these types of incremental literacy are needed for learning new generalities and enhancing the grouping capacities of current classes, similar to the two factors of literacy in humans. Regarding the issue of food recognition, druggies diurnal upload food photos from a smart phone from both old and new classes druggies define being classes else, hence it's vital to anticipate that druggies have varied ideas about the same classThere are a significant amount of new food identifiers as a result of the recent increase in the ability for food to be popular on social media, television programs, food blogs, etc sometimes referred to as food porn(1). However, the majority of traditional approaches to food recognition start with fixed datasets and significant initial class diversity. Although open-ended continuous learning may be used to address food recognition in real-world contexts, there are several difficulties that need to be explored.

II. RELATED WORK

By predicting and rationalizing the outcomes in accordance with demands and user profiles, Ghalib Ahmed Tahir and Chu Kiong Loo 2021, established a user-centered explainable artificial intelligence (AI) framework to strengthen the confidence of the concerned parties. As a nutritional evaluation app, Framework is thorough since it recognizes Food/Non-Food, food categories, and substancesBy employing the Relief F approach to rank features, this study effort reduces the dimensionality of the recovered features. The model's calculations are more challenging due to its redundant properties. Getting a training accuracy of 98 percent and a validation accuracy of 92% results in the best epoch..

V. Lomonaco and D. Maltoni , Recent research has demonstrated that deep models may be trained sequentially on a variety of discontinuous tasks using architecture, regularization, and rehearsal procedures without forgetting prior information. Then, a novel strategy—designated as AR1—fusing architectural and regularization tactics is expressly suggested. Online learning is a good fit for AR1 because of its very low overhead (in terms of memory and compute). When evaluated on CORe50 and iCIFAR-100, AR1 performed significantly better than the currently used regularization techniques.

Chu Kiong Loo, Ghalib Ahmed Tahir, 2021, The potential of food identification systems to estimate dietary intake objectively has lately attracted a lot of research interest in the relevant subject. The structure which recognizes Food/Non-Food, food categories, and ingredients, is complete in terms of a diet evaluation app. For ingredient detection, experimental findings using freshly donated Malaysian food dataset and industry-standard food standards showed greater accuracy on a combined set of metrics.

III. PROPOSED SYSTEM

The mapping nodes for ARCIKELM that best reflect the class can be chosen using an online clustering approach such a reduction in catastrophic error and noise invariance might occur when the input for classification is positioned far from the current neurons, but self-scaling of computing power in a cloud-based setting is the other way, and it's also possible to choose the nearest nodes during classification showed the name, nation, and ingredients of the dish. Additionally, it indicates if the dish is fatty or healthful.

IV. METHODOLOGY

The suggested approach takes into account two facets of unrestrained learning. 1) Gradual in-class instruction 2) Incremental learning guided by data. It consists of three parts. Feature selection in module B, feature extraction in module A, and classification in module C. Each incoming picture is transmitted to the chosen deep feature extraction module throughout the training phase, which then gathers the features. The best characteristics are picked in accordance with our suggested strategy after they are rated using the Relief F technique This work makes use of the innovative ARCIKELM, which meets both requirements for open-ended continuous learning while learning from these representations. In cases when picture representations fall within the novel class, it inserts additional output and hidden neurons. If they come from pre-existing classes, our suggested technique updates the model progressively and only adds additional hidden neurons as needed. The test image's features are taken from it during the classification stage using the same deep feature extractor. Depending on how the Relief F technique's attributes were ranked, the best representations are picked. The ultimate choice is made by ARCIKELM.

The ELM base classifier is trained using the ELM_1 starting set of classes. Using an incremental method with labeled data from both the new and old classes, ELM_1 is modified to correspond to the new classifier ELM_2 when it appears. ELM's internal structure is altered, the neural network receives more output neurons. The following is a statistical development. After a dataset of size d has finished its training phase. The above equation is first used for calculating the result of weight in accordance with the ELM method

$\beta 0 = k_0^{-1} H^T{}_0 T_0$-----(1)

where,

$$H_0 = \begin{bmatrix} G(a_1, b_1, x_d) & \cdots & G(a_1, b_1, x_1) \\ \vdots & \cdots & \vdots \\ G(a_1, b_1, x_n) & \cdots & G(a_n, b_n, x_n) \end{bmatrix}$$
$$and\ T_0 = \begin{bmatrix} t_1^T \\ \vdots \\ t_n^T \end{bmatrix} \ and\ K_0 = H_0^T H_0 \qquad (2)$$

Equation (3) is used to compute H1 from the new class dataset.

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$$H_1 = \begin{bmatrix} G(a_1, b_1, x_s^1) & \cdots & G(a_1, b_1, x_s^1) \\ \vdots & \cdots & \vdots \\ G(a_1, b_1, x_s^n) & \cdots & G(a_n, b_n, x_s^n) \end{bmatrix} \qquad (3)$$

Now, Equation (4), m+1-dimension, in which m is the total amount of columns in T0, represents the number of samples in T1.

$$\mathbf{T_1} = \begin{bmatrix} \mathbf{0} & \cdots & \mathbf{0} & \mathbf{1} \\ \vdots & \ddots & \vdots & \vdots \\ \mathbf{0} & \cdots & \mathbf{0} & \mathbf{1} \end{bmatrix}_{\mathbf{N_1 * (m+1)}} \qquad (4)$$

By integrating the d and s information sets, Equation (5) is used to determine 1.

$$\beta_1 = K_1^{-1} \begin{bmatrix} H_0 \\ H_1 \end{bmatrix}^T \begin{bmatrix} T_0 \cdot M \\ T_1 \end{bmatrix} \qquad (5)$$

here M, which is represented by Equation (6), is a modification matrix.

$$M = \begin{bmatrix} \mathbf{1} & \cdots & \mathbf{0} & \mathbf{0} \\ \vdots & \ddots & \vdots & \mathbf{0} \\ \mathbf{0} & \cdots & \mathbf{1} & \mathbf{0} \end{bmatrix} \qquad (6)$$

It is clear that 1 is computed using incremental learning without the need of a prior dataset.

There are a set number of hidden neurons, which is a big limitation. This makes neurons more flexible and causes catastrophic forgetfulness. There are more neurons needed to process fresh incoming data when new classes are introduced. A set number of neurons causes underfitting, though. Similar to this, overfitting of the data occurs when a high number of hidden neurons are first provided. This issue has been resolved using adaptive CIELM. But the considerable testing done for this research demonstrates that their approach is unstable. We believe that this is a result of the random input weights' low generalization capacity.

1. 1st phase: Data collection is a method of gathering and analyzing knowledge using software that is easily available. The information utilized to train transformer models is crucial Gathering information, which comprises locating Before performing any analysis, it is necessary to collect organized quantitative data. A group of people with the same ailment were the subjects of the data collection. This step is crucial in building high-performance models since the outputs of the models are only as effective as the data upon which they are built the researcher has also created a number of datasets on other countries, such as India, Pakistan, China, Japan, and Korea.

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2. 2nd phase: Data Processing Image Data for Training frequently contains various flaws or garbage values that may be fixed by detecting whether any values are missing from the data and when a specific range of values must be met. If a variable contains many values that are absent, it needs to be deleted. Although cleaning the picture data won't increase the model's accuracy, it will at least lessen any negative effects.
3. 3rd phase: Classification performance is a well-liked indicator for evaluating the effectiveness of the model based on projected class labels. Despite not being ideal, classification accuracy is a great place to start for many classification projects. The best method for assigning predetermined labels for classes to examples of input data will be determined using the data set used for training. The training collection of food images should include many instances of each classifier and be illustrative of the topic at hand.
4. 4th phase: I Although it is a machine learning approach with approximate parameters that might include hundreds of thousands to millions of individuals, generally speaking, training it from the start on a constrained set using food image data will only lead to overfitting. The use of a trained model at the outset is more advantageous and then maximize the method by using just a tiny part of the healthy food image collection.
5. 5th phase: Validation A model is often validated after it has been trained. It entails assessing the trained model against a test dataset in order to ascertain whether or not the assignment is successful on the dataset that has been supplied. Additionally, it examines the system outputs that are being used to evaluate the model's results.

V. ARCHITECTURAL DESIGN OF SYSTEM

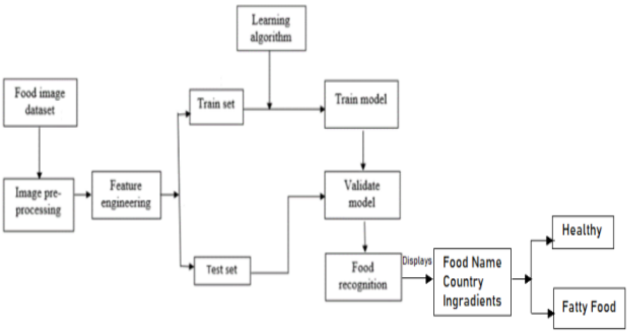

Figure 1: System Architecture

VI. IMPLEMENTATION

Figure 2: Menu

Menu consists of Input Data, Pre-processing, Feature Extraction, Recognition

Figure 3: Read Image

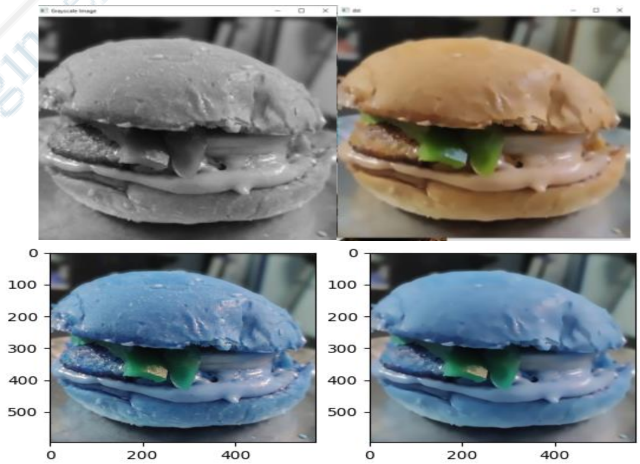

Figure 4:Preprocessing

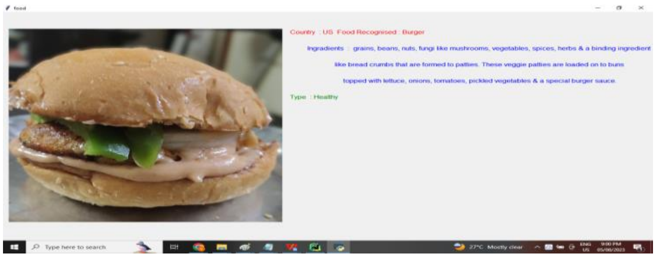

Figure5: Classification And details

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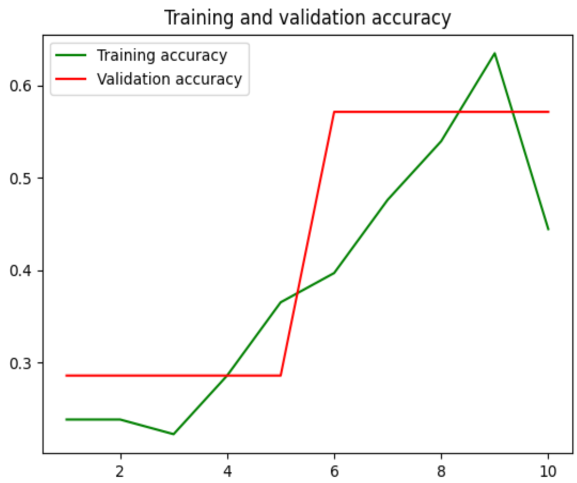

Figure 6: Accuracy graph

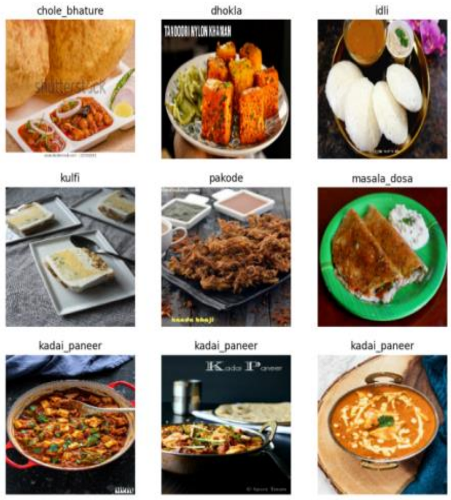

Figure 7: Food Dataset

Consists of 6269 files belonging to 20 classes.
Using 1880 files for validation.

Figure 8: Feature Extraction

Feature extraction is a dimensionality decrease approach that breaks and condenses a beginning collection of raw data into smaller, simpler groupings. Processing will be easier as a consequence. The most important characteristic of these massive data sets is the large number of distinct variables they include. It requires a lot of processing resources to process these variables. By selecting and merging variables into features, feature extraction assists in extracting the best feature from such enormous data sets in order to efficiently minimize the amount of data. These features properly and distinctively describe the actual data set while being straightforward to utilize.

VII. CONCLUSION

The food identification data is an unstructured, dynamic set of data. Food lessons and sampling are continually expanding. Existing deep learning models for the identification of foods make the initial assumption that all food categories and subclasses of foods exist. They go through terrible forgetfulness when learning in class. These issues are addressed in this study's proposal of an innovative framework for open-ended continuous learning for food identification. Relief F is utilized to order and select features, new deep learning networks are utilized to extract features, and ARCIKELM is utilized for categorizing data. This work considers the good generalizability of deep model features for feature extraction. In order to determine the appropriate length, the Relief F strategy was utilized. Results demonstrate that this method cuts the recommended classifier's total training period for all datasets by 52.14%.The approach used a unique dynamic decreased classes incrementally core with extreme learning machines for handling the complex nature of data incremental learning and class incremental learning. Both output neurons and hidden neurons are dynamically increased. Catastrophic forgetting is lessened by the prior neurons lower adaptability. Experimental results on four categorization performance indicators and five catastrophic forgetting metrics show that the proposed classifier performs on par with batch classifier, beats the present ACIELM and CIELM, and exceeds both. The suggested framework outperforms competing food recognition systems as while fulfilling the standards of open-ended continuous learning, under the supervision of extreme learning a group, PMTS, GTBB, and others.

VIII. FUTURE WORK

The mapping nodes for ARCIKELM that best reflect the class can be chosen using an online clustering approach such a self-organized incremental neural network, which may also be applied to classify data by selecting the nearby nodes. In a cloud context, resources for computers scale automatically in the other direction. The amount of processing resources required rises when innovative classes and new photos are introduced. The user demands also fluctuate at various times throughout categorization. In order to accomplish this, the unrestricted continual because of the noise, it can minimize forgetfulness that is disastrous. Earning framework must be capable of autonomously scaling its computational assets within a cloud environment. Finally, more research will improve the suggested framework for comprehensible AI.

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