Pattern Based Multivariate Regression using Deep Learning (PBMR-DP)
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Abstract

We propose a deep learning methodology for multivariate regression that is based on pattern recognition that triggers fast learning over sensor data. We used a conversion of sensors-to-image which enables us to take advantage of Computer Vision architectures and training processes. In addition to this data preparation methodology, we explore the use of state-of-the-art architectures to generate regression outputs to predict agricultural crop continuous yield information. Finally, we compare with some of the top models reported in MLCAS2021. We found that using a straightforward training process, we were able to accomplish a MAE of 4.394, RMSE of 5.945, and $R^2$ of 0.861.

1. Introduction

In the recent years, Machine Learning algorithms have been improving dramatically in different areas. Unsupervised methods have been incorporated in the deep learning field to solve image-based problems, sound, and text. We also notice that neural network architectures have changed and consequently, they have changed the training process. But sometimes, the innovation blinds some improvement in promising ideas that were not developed to a higher potential. Here, we present our work that combines state-of-the-art image architecture and regression.

Inspired by the data provided in [12], a sensor dataset containing information of multiple sensors with timestamp. We decided to take a different approach and explore the conversion of this dataset into images (Section 3.1). This conversion opens the doors of Computer Vision (CV) models for tabular data. First, we explored the conversion of sensor data into an accurate image-like data, and then make changes in the neural network architecture as common CV architectures do not tend to give regression as output which was the case for our model. This allows us to perform Multivariate regression [1] which is pattern-driven instead of data-driven.

1.1. Contribution

In this work, we present two major contributions. The first one is constructing sensors-to-image conversion in which tabular data can be represented as an image. This facilitates the use of modern Computer Vision architectures.
Secondly, using these sensors-to-image samples to predict continuous crop yield values.

2. Related Works

Another factor for using images was that we did not want to base our architecture on long short-term memory (LSTM), which usually takes a lot of resources to perform the training process. This led us to do exploration over methods that involved images and regression. To start, we explore the idea around image age detector, which affirmed our concerns [10] works with the creation of two Convolutional Neural Networks (CNNs), one to predict gender and another for age prediction with the quality classifier instead of a regressor. In practice, there is not much done in terms of having a regression output from an image-based model.

Finding that many approaches to what, in our knowledge, are regression problems have in common the characteristics of converting it to a classification problem led us to explore other fields. We started by looking at [4], in which they work on a network able to predict the rotation angle of given images. A similar idea can be seen in [8], which shows a CNN regression framework for predicting 3D pose estimation.

In another hand, we explore the conversion of sensor data into images such as [16]. The data was also serialized in such work and represented different factors that we did not have to deal with. Therefore, their conversion was more complex than in this work, but the idea of generating these images is viable.

The use of convolutional neural networks in image classification has become the standard of the day. The image classification revolution began with the use of deep neural networks - AlexNet [7].

The Inception models which are carefully customized multi-branch architectures with carefully designed branches. Resnet, Resnexts and EfficientNet are two branch networks where one branch is identity mapping.

The melspectogram Image generated using the Librosa [9] package allows for classifying sounds based on patterns. Visualizing sound as an Image [3, 13] with deep neural networks improves accuracy and reduces computational requirements from classical methods of event or pattern recognition [6].

Time series data becomes complex when the number of sensors and the frequency of data recording increases. The current solution is regression to find the best fit based on the multivariate data. Early proposed solutions require the conversion and generation of custom CNN like a 2 stage CNN proposed in [2]. The usage of detecting patterns requires much pre-processing with feature engineering. The process is time-consuming and will require extensive study of the correlation of each input date with the training data.

3. Method
3.1. Input Data

Traditionally all data to Machine Learning has to be pre-processed and statistically analyzed extensively with weights before using them as input data. The extensive process is time-consuming and requires human and computer resources to verify the correlation of the data to the output it is being trained with. Our approach exploits the ability of the Deep Neural Networks Feature learning segment to learn the weights on its own, allowing us to skip the entire pre-processing stage.

Our data preparation method from tabular data allows it to be fed directly to most of the CNNs, if not all, without changing anything. The tabular data used must be across a common axis of measurement, for example time series or measured at the same interval. If any values are missing in the tabular data, we will use the immediate past data to fill the missing blank in the table. This property of time series data helps ensure noise is reduced to a minimum in the input data. The generated Tabular data is normalized row-wise based on the absolute range of measured variable.
### Table 1. Performance metrics with different standard models using different Optimizers. All models run with the learning rate and batch size specified in Section 4.

| Models            | MAE ↓ | RMSE ↓ | $R^2$ ↑ |
|-------------------|-------|--------|---------|
|                   | SGD   | Adam   | LARS    | SGD   | Adam   | LARS    | SGD   | Adam   | LARS    |
| ResNet 50         | 4.529 | 5.496  | 4.644   | 5.963 | 7.258  | 6.266   | 0.849 | 0.792  | 0.845   |
| EfficientNet B0   | 5.535 | 5.232  | 6.577   | 7.312 | 6.958  | 8.586   | 0.789 | 0.809  | 0.709   |
| ResNext 50        | 4.394 | 5.371  | 5.191   | 5.945 | 7.118  | 6.889   | 0.861 | 0.799  | 0.812   |

### Table 2. Comparison with the models submitted in MLCAS2021 Challenge using the same evaluation metrics.

| Competition Teams | Model approaches                  | Performance |
|-------------------|-----------------------------------|-------------|
| QU(exp006)        | Statistical Modelling             | MAE ↓ 4.41  |
|                   |                                   | RMSE ↓ 5.89 |
|                   |                                   | $R^2$ ↑ 0.87|
| CUFE              | ensemble Regression               | MAE ↓ 4.42  |
|                   |                                   | RMSE ↓ 5.95 |
|                   |                                   | $R^2$ ↑ 0.86|
| Star              | M/4* 1D CNN with Ensemble         | MAE ↓ 4.47  |
|                   |                                   | RMSE ↓ 5.95 |
|                   |                                   | $R^2$ ↑ 0.86|
| Elendil           | M/7 * 1D CNN with Ensemble 5      | MAE ↓ 4.47  |
|                   |                                   | RMSE ↓ 5.95 |
|                   |                                   | $R^2$ ↑ 0.86|
| AA2               | XgBoost                           | MAE ↓ 4.6   |
|                   |                                   | RMSE ↓ 6.15 |
|                   |                                   | $R^2$ ↑ 0.85|
| Ours              | ResNext 50 - SGD                  | MAE ↓ 4.39  |
|                   |                                   | RMSE ↓ 5.94 |
|                   |                                   | $R^2$ ↑ 0.86|

Fig. 1 shows how the data can be visualized with patterns.

\[
\overrightarrow{x}_{ij} = \frac{x_{ij} - \sigma(s_i)}{\lambda(s_i) - \sigma(s_i)}
\]

where \(\overrightarrow{x}_{ij} \in [0, 1]\) is the normalized data point at positions \(i, j\). The values in \(x_{ij}\) represent the original tabular data in which \(i\) represents the row (our sensor), and \(j\) the time in our dataset. In addition, \(\sigma(s_i)\) and \(\lambda(s_i)\) represent absolute minimum and maximum values of sensor \(s_i \in S\) where \(S\) is the set of all the sensors.

The generated data (Fig. 1) is fed into the Models to look for features and patterns instead of solving for the values. This approach allows us to maximize the learning ability of neural networks instead of trying to solve the best fit method. The slow trial and error of assigning a range of values to a pattern seen or observed by the Model instead of solving the best equation for a set of time-based variables.

### 3.2. Architecture Design

The Model relies on the feature learning/pattern recognition model of the Convolutional Neural Networks. Since they are heavily used in classification models, the idea was to modify a few layers to convert them into a regression pattern model, which outputs a single regression yield output instead of class probability with softmax. The base architecture can be found in Fig. 2.

Instead of classification, we introduce an Adaptive Concat pool layer right after the feature learning layers to understand regression data. Adaptive Concat Pool combines the AdaptiveAvgPool and AdaptiveMaxPooling layers defined in the PyTorch framework. This custom layer allows us to convert the problem into a Fully Connected Model (FCN) approach to the regression values. The use of deep Neural networks with different optimizers and fixed hyper tuning allows us to maximize the results in the least time.

The new and connected layers modified the following state-of-the-art models to create a single output for each 2D input.

**Residual Network (Resnet):** The addition of shortcut connections in each residual block enables gradient flow directly to the bottom layers. Resnet [5] allows for extremely deep structures for state-of-the-art object detection performance, which is used as the baseline model for the entire approach of using 2D data in regression. Initial use case with default parameters from torchvision models shows comparable performance and results to current solutions in the domain of Yield Estimation.
Regression Analysis Techniques | Performance
--- | --- | ---
| | MAE ↓ | RMSE ↓ | R² ↑ |
Linear Regression | 6.100 | 8.121 | 0.740 |
Elastic Net | 9.103 | 11.548 | 0.471 |
LASSO | 9.987 | 12.790 | 0.363 |
SVR-RBF | 5.976 | 7.875 | 0.758 |
Stacked-LSTM | 5.484 | 7.276 | 0.792 |
Temporal Attention | 5.441 | 7.239 | 0.795 |
Ours | **4.394** | **5.945** | **0.861** |

Table 3. In this table we tabulate the different performance metrics on the Soybean Crop Yield Data performed using the published ML models.

EfficientNet: To demonstrate the effectiveness of scaling on both depth and resolution aspects of the existing CovNet model, a new and more mobile size baseline was designed called EfficientNet [14]. The Neural Architecture was focused on optimizing the accuracy and FLOPs required to detect the same images.

ResNext: In addition to the dimensions of depth and width of ConvNet, the paper introduces “Cardinality,” a definition for the size of transformations. Allows controlling the “Network-in-Neuron” to approach optimal results in the process. Makes significant accuracy improvements on Popular ConvNets hence named as ResNext [15].

3.3. Reduced Feature Engineering

Normalizing the sensors to their absolute ranges allows us to generate data in a floating-point range of 0-1. We use the fact that neural networks try to figure their weights based on patterns learned. We can reduce the feature engineering required on new datasets by exploiting this basic property. Allows for faster data modeling tasks and simpler training loops with new data. As proved in the 2, the dimension and data type will no longer constrain the models. Understanding the correlation of inputs and their impact on the output can now be left for the Model to decide.

4. Experiment

In the following section, the proposed Data Usage approach is evaluated with different state-of-the-art machine vision models. An ML tool chain was created to perform continuous tests in similar data settings and hardware setup. We conducted an ablation experiment on Crop Yield Regression Task [12]. It is a multi-variate regression problem with 7 daily variables measured over a fixed time period of 214 days. The models where run in a Intel i9-10900k CPU with 128 GB 2666MHz Ram and NVidia RTX 3090 with 24 GB VRAM. The data set produced image size of 214x7 which allowed to run multiple models simultaneously to produce maximum results.

Throughout the experiments, the learning rate is set to $1e^{-03}$ with a batch size of 128 and the loss after trial and error was fixed to MSEloss or L1loss. The modelling was programmed in python 3.8 using the pytorch framework [11].

We follow [5, 14, 15] to construct the Feature learning stage of the models (depth). The pooling layer is modified to a custom AdaptiveConcat Layer with Fully connected layers pointed to a single output.

4.1. Experiments on Crop Yield Dataset

The extensive samples of the crop yield with 93000 samples allow the Model to learn behaviors very well. The data consists of 7 weather variables, namely Average Direct Normal Irradiance (ADNI), Average Precipitation (AP), Average Relative Humidity (ARH) Maximum Direct Normal Irradiance (MDNI), Maximum Surface Temperature (MaxSur), Minimum Surface Temperature (MinSur) and Average Surface Temperature (AvgSur). The secondary inputs are also provided for each data point: Maturity group (MG), Genotype ID, State, Year, and Location. Each data frame points to a ground truth which is the yield.

4.2. Performance Metrics

Unlike the accuracy metrics, which are usually associated with CNN, to define the regression, the standard metrics such as Mean Average Error (MAE), Root Mean Square Error (RMSE), and $R^2$ to evaluate the performance. The loss used in the process is MSEloss or L1loss in the PyTorch framework. In order to combat over-fitting the data to training data, k-cross-validation is performed, and significant improvements are noted in the areas of blind tests.

5. Results and Discussion

Comparison with different models: Table 1 shows in depth testing done with the different state of the art models with the parameters: Learning rate = $1e^{-03}$, batch size = 128, loss function = pytorch.MSELoss. The models were run for different optimizers, and the results were tabulated. It was found that the ResNext50 with SGD optimizer per-
formed the best out of the box with the same hyperparameters due to presence of cardinality.

Comparing Competition approaches: Table 2 shows the performance of different online teams from the MCLAS Challenge. The best models were shown in the online leaderboard and available publicly for the challenge. They were better than the research paper the research was established upon. The techniques involved heavy statistical analysis and feature engineering in multiplying the number of available features to improve learning parameters for the data. Most of the results involved using ensemble techniques to combine weights generated using different models to get the best results. Our approach is simpler with just the deep neural network modified to become a regression model with a custom data loader to convert Real-time data into an image type array.

Comparison with state-of-the-art results: Table 3 shows the crop yield prediction dataset results. Our results prove a dramatic increase in prediction performance with a simple change in how data is used. In addition, our model approach allows for faster data to model regression without the need for analysis of the correlation between the inputs and the output.

6. Conclusion

This work provides a pattern based approach for multivariate regression. With our sensor-to-image conversion, we bring computer vision techniques to regression tasks. Our experiment with multiple models and different optimizers proves the validity of our method. We have been able to outperform every classical approach and are at par with the best ensemble methods.

With our approach, we hope to make significant impact with tabular data and advance the research even further in these areas.

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