Multi-script Handwritten Digit Recognition
Using Multi-task Learning

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Abstract. Handwritten digit recognition is one of the extensively studied area in machine learning. Apart from the wider research on handwritten digit recognition on MNIST dataset, there are many other research works on various script recognition. However, it is not very common for multi-script digit recognition which encourage the development of robust and multipurpose systems. Additionally working on multi-script digit recognition enables multi-task learning, considering the script classification as a related task for instance. It is evident that multi-task learning improves model performance through inductive transfer using the information contained in related tasks. Therefore, in this study multi-script handwritten digit recognition using multi-task learning will be investigated. As a specific case of demonstrating the solution to the problem, Amharic handwritten character recognition will also be experimented. The handwritten digits of three scripts including Latin, Arabic and Kannada are studied to show that multi-task models with reformulation of the individual tasks have shown promising results. In this study a novel way of using the individual tasks predictions was proposed to help classification performance and regularize the different loss for the purpose of the main task. This finding has outperformed the baseline and the conventional multi-task learning models. More importantly, it avoided the need for weighting the different losses of the tasks, which is one of the challenges in multi-task learning.

Keywords: Multi-script · Handwritten Digit Recognition · Multi-task Learning · Amharic Handwritten Character Recognition

1 Introduction

Handwritten digit recognition is commonly known to be the “Hello World” of machine learning. Accordingly, it has been studied widely for different languages\cite{21,17,12}. However, this is not the case for multi-script digit recognition works that encourage the development of robust and multipurpose systems. Whereas in practice it is possible to see multiple scripts in a document. More importantly working on multi-script recognition opens a way for multi-task learning.
(MTL), considering the script classification as an auxiliary task for instance. Deep learning methods proved to show a very good recognition performance on such classification tasks. Apart from the success stories of recognition performance, the requirement for large amount of data, the issue of over-fitting, and computation cost of the complex models has remained a challenge in the area of deep learning. On the other hand the introduction of multi task learning seems to have resolutions for that. With multi-task learning one can address multiple problems reducing the requirement of having individual models\[29\]. On top of this, it has shown to be good at regularizing the models which prevent from over-fitting\[27\]. One can also use advantage of multi-task learning to increase amount of dataset which is usually required in machine learning. However, multi-task learning by itself is not free from challenges. Combining the losses of the different tasks, tuning the hyper-parameters, and using the estimate of one task as a feature to another task are the major challenges in multi-task learning\[18\].

In this study we make use of multi-task learning and also avoid one of the challenges which is combining the different weighted losses. First we will introduce the formulation of a multi-task learning setting from the individual tasks. The motivation behind this formulation is to bring the problem of Amharic, Indian, Japanese, and related character recognition \[14,17,4,28\] to a more general setting so that researchers contribute to the solution with ease. In these languages the alphabets can be organized in a matrix form where one can exploit the information available over the rows and columns as they exhibit similarities, Fig. 1,2,3. Since there is no baseline with this method, we aim at presenting an exploratory investigation towards a higher a goal. Hence, in this study we organize the main task (classifying the exact label) in to additional rows and columns of different classification tasks as shown in Table 1. All these digits are Hindu–Arabic numeral systems where the widespread Western Arabic numerals are used with Latin scripts whereas the Eastern Arabic numerals are used with Arabic scripts. However, Kannada with its own script is the official and administrative language of the state of Karnataka in India \[7,21\]. In this study, this general method will also be applied to the specific case of Amharic handwritten character recognition.

Finally we will compare three models. The first one is a baseline model to classify each label as a thirty class (3scripts × 10digits) classification problem. Using a related task as an auxiliary task for MTL is the classical choice\[25\]. Hence, the second model employees a conventional multi-task learning considering the classification of the rows (scripts) and columns (digits) as auxiliary tasks. The third one which is the proposed model also applies multi-task learning however with a new way of controlling and exploiting the information contained in the related tasks. This is basically done by creating a four class classification problem as an auxiliary task. The four class labels indicate whether the main task is good at identifying the digit, the language, the label (both digit and language), or none. By doing this we will get the information regarding the training behaviour of the different tasks which can be used to help and control the main task. For this study since we gave emphasis to show the useful formulation and advantage of
multi-task learning, we adapted the ResNet [16] pretrained model to build our models. The rest of this paper is organized as follows: related works are reviewed in the next section. Section 3 outlines the methodology followed for the study and experimental results are discussed under Section 4. Finally, conclusion and future works are forwarded.

Contributions of the Paper:

i. Presents the possible formulation of individual tasks in to multi-task learning setting
ii. Proposes a novel way of exploiting auxiliary tasks to regularize and help the main task
iii. Demonstrates the proposed method on the specific case of Amharic handwritten character recognition

![Fig. 1. Parts of Amharic alphabet.](image1)

![Fig. 2. Parts of Devanagari alphabet.](image2)

![Fig. 3. Parts of Japanese Hiragana alphabet.](image3)

2 Related Works

There are some related works on multi-script recognition and a few of them employ multi-task learning. Sadeghi et al. [26] performed a comparative study
between a monolingual training and bilingual training (Persian and Latin digits) using deep neural networks. They have reported the superior performance of bilingual networks in handwritten digit recognition, thereby suggesting that mastering multiple languages might facilitate knowledge transfer across similar domains. Bai et al. [8] proposed shared-hidden-layer deep convolutional neural network (SHL-CNN), the input and the hidden layers are shared across characters of different tasks while the final soft-max layer is task dependent. They have used Chinese and English superimposed texts and show that the SHL-CNN reduce recognition errors by 16-30% relatively compared with models trained by characters of only one language. Maitra et al. [19] employed six databases: MNIST, Bangla numerals, Devanagari numerals, Oriya numerals, Telugu numerals and Bangla basic characters. They used the larger class (Bangla basic characters) pretrained on CNN as a feature extractor with aim to show the transfer learning that result in a good performance of other scripts with smaller class. All of the above mentioned works didn’t address to balance the effects of the related tasks.

Multi-Task Learning (MTL) is a learning paradigm in machine learning and its aim is to leverage useful information contained in multiple related tasks to help improve the generalization performance of all the tasks [29]. Technically, it is also optimizing more than one loss function in contrast to single-task learning. We can view multi-task learning as a form of inductive transfer. Inductive transfer can help improve a model by introducing an inductive bias provided by the auxiliary tasks, which cause the model to prefer hypotheses that explain more than one task [29]. According to Zhang et al. [29] MTL algorithms are classified into five categories: feature learning (feature transformation and feature selection approaches), low-rank, task clustering, task relation learning, and decomposition. The widely used approach of MTL including this study is homogeneous MTL and parameter based MTL with decomposition approach. In this case the tasks are decomposed with their relevance and usually the main task remains unpenalized. Zhang et al. [29] suggest the decomposition as a good MTL approach with the limitation of the black box associated with coefficients and forward future work emphasize its formalization since there is no guaranty that MTL is better than single task.

Ruder [25] introduced the two most common methods for MTL in Deep Learning, soft parameter sharing and hard parameter sharing. As in most computer vision tasks this study uses hard parameter sharing where the hidden layers between all tasks are shared while keeping task specific output layers.

Table 1. Organization of the individual tasks in to multi-task settings.

| Script       | Digit1 | Digit2 | Digit3 | Digit4 | Digit5 | Digit6 | Digit7 | Digit8 | Digit9 | Digit10 |
|--------------|--------|--------|--------|--------|--------|--------|--------|--------|--------|---------|
| Latin        |        |        |        |        |        |        |        |        |        |         |
| Arabic       |        |        |        |        |        |        |        |        |        |         |
| Kannada      |        |        |        |        |        |        |        |        |        |         |
The author further stress that only a few papers have looked at developing better mechanisms for MTL in deep neural networks and our understanding of tasks, their similarity, relationship, hierarchy, and benefit for MTL is still limited. Since multitask learning models are sensitive to task weights and task weights are typically selected through extensive hyperparameter tuning, Guo et al. introduced dynamic task prioritization for multitask learning. This avoids the imbalances in task difficulty which can lead to unnecessary emphasis on easier tasks, thus neglecting and slowing progress on difficult tasks.

Research works on Amharic document recognition in general lack combined efforts mainly due to unavailability of publicly available standard dataset. Accordingly different techniques are applied in different times without tracing and following a common baseline. It is worth mentioning the work done by Assabie et al. [6] for handwritten Amharic word recognition. Betselot et al. [23] also worked on handwritten Amharic character recognition. Both works used their own datasets and employed conventional machine learning techniques. Recently there are some encouraging works emerging on Amharic character recognition applying deep learning techniques. The different authors emphasized on different types of documents including printed [2, 9, 13], ancient [20, 11], and handwritten documents [14, 14, 1]. Accordingly the research efforts in this regard lack complementing each other and improving results based on a clear baseline.

3 Methodology

This section outlines the dataset preparation and organization of the models for the experiments.

3.1 Dataset Preparation

We have used the publicly available datasets MNIST [24], MADBase [12], and Kannada MNIST [21] for Latin, Arabic, and Kannada handwritten digit scripts respectively. All these datasets are 28 × 28 pixel size images and they have equal size of data-sets which is 60,000 for training and 10,000 for test. We have used 16% of the training set for validation with a balanced stratified split.

The dataset for Amharic handwritten character recognition experiment was organized from Assabie et al. and Samuel et al. [5, 14]. It was organized to 77 characters with 11 (row) by 7 (column) tabular structure as shown in Table 2. This is done intentionally to minimize the number of classes as compared to the number of samples available per character, that is 150. Another reason is to see the application of the proposed method in a balanced dataset setup on visually similar characters.

3.2 Organization of the Experiments

In this study the main task is to classify each label from all the three scripts. That is, a trained model is expected to classify each image as it is “X digit
Table 2. 77 visually similar Amharic characters.

| ñë | dë | u | i | ø | e | o |
|----|----|---|---|---|---|---|
| b  | h  | k | n | y | a | k |
| n‘ | p‘ | t’ | n | y | a | k |
| l   | n   | n‘ | n   | n   | n | n   |
| b   | h   | k | n | y | a | k |
| b   | h   | k | n | y | a | k |
| b   | h   | k | n | y | a | k |
| b   | h   | k | n | y | a | k |
| b   | h   | k | n | y | a | k |
| b   | h   | k | n | y | a | k |
| b   | h   | k | n | y | a | k |

from Y script”. Hence, our baseline model will be a thirty class (3 scripts × 10 digits) classification model, the blue line in Fig. 4. Another baseline is the usual multi-task learning, the outer rectangle in Fig. 4, which uses the advantages of reformulating the main problem in to other two auxiliary tasks. The third approach, proposed, will introduce a novel way of integrating multi-task learning to extract relevant information from the auxiliary tasks while balancing the effect on each other. From the usual multi-task learning we show the optimum performance by tuning the loss weights which is better than the first baseline 30 class vanilla model. For the sake of just giving a glance on how the specialized models perform, we have also experimented the three independent single task models. All the experiments conducted in this study are described in Table 3.

The proposed method removes the two auxiliary tasks and introduces a one reformulated auxiliary task instead. That is a four class classification problem including getting both the row and column (the label), only the row (language), only the column (digit), and missing both. This information can be obtained from the main task itself by converting the predicted label in to row and column using the formulas row = label div 10 and column = label mod 10 respectively. This helps to learn the properties of the characters like how they confuse the model during the training with out affecting each other. We give highest number that is 3 as a label for getting both rows and columns which in turn signals over fitting. We also add this numbers with in batches to use as a factor to be multiplied to control the loss of the main task. That is the more we know this label the more the loss will be. Therefore, the model prefers to minimize the second loss instead. That is predicting the properties of the characters in to four classes. This balances and controls the whole training process.

Likewise for Amharic handwritten character recognition the same procedure will be followed. Here the row will be 11 instead of 3 and the column will be 7
instead of 10. The $3 \times 10 = 30$ class classification problem will now be $11 \times 7 = 77$ class classification problem in the case of Amharic characters.

![Diagram of models structure](image)

**Fig. 4.** Models Structure. Blue line shows the baseline model, the outer rectangle shows the multi-task models, and the inner rectangle represents the individual (single task) model.

\[
L_{\text{Base}} = l(y, \hat{y}) \\
L^{W\text{Loss}} = l(y, \hat{y}) + \sigma_1 \cdot l(y_1, \hat{y}_1) + \sigma_2 \cdot l(y_2, \hat{y}_2) \\
L^{\text{New}} = \text{factor} \cdot l(y, \hat{y}) + l(y_a, \hat{y}_a)
\]

where in all the equations $y, y_1, y_2, \hat{y}, \hat{y}_1, \hat{y}_2$ are the ground truth and prediction of their respective label, digit, and script classes and $l$ is Cross Entropy Loss.

### 4 Experimental Results

Due to our emphasis to show the useful formulation and advantage of multi-task learning over individual tasks, in all the models in these experiments we have adapted the ResNet pretrained model from torchvision.models. We have used a mini batch size of 32 and Adam optimizer. All these configurations are kept unchanged between the individual, baseline, and the multi-task models. All the experiments were performed using Pytorch 1.3.0 machine learning framework on
Table 3. Description of the different models in the experiment.

| Model Name | Equation | Description |
|------------|----------|-------------|
| Lat        | (1)      | Single task model trained on the Latin digits |
| Arab       | (1)      | Single task model trained on the Arabic digits |
| Kan        | (1)      | Single task model trained on the Kannada digits |
| Base       | (1)      | Single task model trained on all the three scripts |
| Wloss      | (2)      | Multi-task model with weighted loss of 0.2,0.65 for sigma 1 and 0.3,0.35 for sigma 2 for multi-script and Amharic recognition respectively |
| New        | (3)      | The newly proposed model |

GPU nodes connected to computing cluster at Information Systems and Machine Learning Lab (ISMLL), University of Hildesheim.

Each model run up to 100 epochs three times. The average result on test sets from the three evaluations by each model are presented in Table 4. The accuracy and loss curves of the four competing models (baseline, conventional multi-task, and proposed multi-task model) are shown in Fig. 5 for multi-script recognition and in Fig. 6 for Amharic recognition. Further Fig. 7 show how the proposed multi-task model regularizes the main task as compared to the conventional multi-task learning.

Table 4. Accuracy score of the models on test sets

| Model | Latin digits | Arabic digits | Kannada digits | Average | Range | Amharic Characters |
|-------|--------------|---------------|----------------|---------|-------|--------------------|
| Lat   | 98.45        | 0             | 0              | -       | -     | -                  |
| Arab  | 0            | 98.49         | 0              | -       | -     | -                  |
| Kan   | 0            | 0             | 96.25          | -       | -     | -                  |
| Base  | 97.19        | 95.51         | 94.90          | 95.87   | 2.99  | 73.83              |
| Wloss | 97.18        | 97.94         | 96.13          | 97.08   | 1.81  | 74.68              |
| New   | 97.85        | 98.07         | 97.23          | 97.71   | 0.84  | 75.91              |

The results from Table 4 show the advantages gained from multi task learning. However, it is expensive to find the optimum sigmas for weighting the different losses in regard to conventional multi-task setting. Whereas the proposed multi-task approach performed best and is shown to be robust enough not to be affected by the auxiliary tasks without a need for these hidden coefficients. This is also likely to be one reason for we see the minimum range between the scores of the proposed model.

As it can be seen in Fig. 7 the proposed model enforces regularization effect for the main task. This can be seen from the oscillating behavior of the auxiliary task while maintaining a relatively smooth curve for the main task. This is an interesting behavior expected since we aim at being good on the main task. The technique incorporates the auxiliary task, their combined contribution, and the usual main task. It is formulated in a such a way that optimizing the loss
Fig. 5. The learning behavior of the models, multi-script.

Fig. 6. The learning behavior of the models, Amharic.

Fig. 7. Regularizing the main task, multi-script.
implicitly observes the main task and enforces the contribution of the auxiliary task agree to the main task. Even though this tie-up is feasible for this particular problem, it is still possible to untie by introducing desired operations that allow the focus on the auxiliary tasks as well when needed. More importantly, this technique from the proposed model can open the opportunity to exploit the learned parameters of the auxiliary task during model evaluation as well. This is not common in the conventional multi-task learning where the parameters of the auxiliary tasks are wasted.

5 Conclusion

This study shows a formulation of multi-task learning setting from individual tasks which can be adapted to solve related problems that can be organized in a matrix way. Therefore, the study addressed multi-script handwritten digit recognition using multi-task learning. Apart from exploiting the auxiliary tasks for the main task, this study presented a novel way of using the individual tasks predictions to help classification performance and regularize the different loss for the purpose of the main task. This finding has outperformed the baseline and the conventional multi-task learning models while avoiding weighted losses which is one of the challenges in multi-task learning. In this paper the proposed method worked for a specific case of Amharic handwritten character recognition. Hence, similar approaches can also be followed to address similarly structured languages.

Finally, we forward future works address similar multi-script multi-task learning problems encouraging the development of robust and multi-purpose systems. The generalization of the proposed model to any type of multi-task settings could also be a good future work to look.

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