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Lloyd Pellatt, Daniel Roggen

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Fast Deep Neural Architecture Search for Wearable Activity Recognition by Early Prediction of Converged Performance

Lloyd Pellatt
lp349@sussex.ac.uk
Wearable Technologies Lab
University of Sussex
Brighton, United Kingdom

Daniel Roggen
daniel.roggen@ieee.org
Wearable Technologies Lab
University of Sussex
Brighton, United Kingdom

Abstract

Neural Architecture Search (NAS) has the potential to uncover more performant networks for wearable activity recognition, but a naive evaluation of the search space is computationally expensive. We introduce neural regression methods for predicting the converged performance of a Deep Neural Network (DNN) using validation performance in early epochs and topological and computational statistics. Our approach shows a significant improvement in predicting converged testing performance. We apply this to the optimisation of the convolutional feature extractor of an LSTM recurrent network using NAS with deep Q-learning, optimising the kernel size, number of kernels, number of layers and the connections between layers, allowing for arbitrary skip connections and dimensionality reduction with pooling layers. We find architectures which achieve up to 4% better F1 score on the recognition of gestures in the Opportunity dataset than our implementation of the state of the art model DeepConvLSTM, while reducing the search time by >90% over a random search. This opens the way to rapidly search for well performing dataset-specific architectures.

CCS Concepts

• **Computing methodologies** → **Neural networks**.

Keywords

activity recognition; neural architecture search; deep learning

ACM Reference Format:
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1 Introduction

Designing a Deep Neural Network (DNN) for Human Activity Recognition (HAR) [49] requires making decisions about many architectural hyperparameters, including layer types, sizes, numbers of and connections between layers. Due to the extremely large space of neural architectures (we explore a search space of 10^{16}), these decisions are often made based on prior experience and limited systematic explorations.

Neural Architecture Search (NAS) has been introduced in computer vision and natural language processing to perform a guided exploration of the search space rather than exhaustive or random [14], using Reinforcement Learning (RL) [27, 39, 51, 57, 58], genetic algorithms [13, 33], or gradient descent [26, 28]. Each has produced results comparable to or better than state-of-the-art models [14].

NAS has not yet been applied to HAR from wearable sensors (see section 2). Convolutional input layers in HAR owe their success as feature extractors to their ability to match sensor signal patterns to activities [54]. This requires the convolutional layers and activities to be well matched (in terms of kernel size, etc.), which is not a trivial proposition given variance in duration of relevant patterns and in sample rates [31]. While recurrent and LSTM networks can be employed to exploit temporal relationships, they tend to perform better when applied after convolutional feature extractors [37].

NAS has the potential to automatically tailor convolutional feature extractors to specific datasets, while remaining dataset-agnostic in principle. The key contributions of this pilot study for the application of NAS to wearable HAR, are:

- A demonstration of the principles of deep RL-based NAS applied to wearable HAR for the first time, evaluated on the Opportunity sporadic activity recognition dataset [15].
- A comparative study of 5 techniques for predicting performance of classifier models in early training epochs, in order to reduce the computational complexity of NAS.
- A discussion of the limitations of the method and of the most important areas where further research is needed.

2 Related Work

Table 1 highlights key network processing layers included in deep networks for HAR, and illustrates the breadth of architectures suggested so far. Convolutional units are a favorite to act as feature extractors, though AE has also appeared. Temporal dynamics are often captured with LSTM, although RNN and BiRNN have also been suggested, and some networks did not include temporal processing.

For the vast majority of the networks reported in table 1, any disclosed search strategy used to determine the topology of the DNN was limited to a grid search over a few different numbers of layers or units per layer ([19] is a counter-example, but their systematic exploration is still limited to ≈ 1,500 configurations while we sample 20,000 per search from a space of 10^{16}). We also found a large range of architecture depths, between 2-10 layers. Those works that provided the number of trainable parameters ranged from 49K to 7M parameters. Each of these network architectures

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Ref	Modalities	Dataset	Components	N_L	N_P
[8]	IMU	SBHAR [43], UniMiB [32], REALDISP [5]	CNN, Pool, Bi-LSTM	5	–
[12]	IMU	PAMAP2 [42], Skoda [53], Opportunity [7]	MLP	5	49K
[45]	IMU, Altitude	HHAR [47], UniMiB, UCI HAR [2], MobiAct [48], WISDM [50], MSense [30]	CNN, Pool, MLP	5	–
[38]	IMU	Ubicomp 08 [21], Opportunity	CNN, LSTM	13	–
[20]	Acc, PIR	Opportunity, CASAS [10], WISDM, Daphnet [3]	MLP	1 –3	–
[29]	Acc, Gyro	Own (Password inference)	AE, RNN, Bi-RNN	4	–
[9]	IMU	Opportunity, UCI HAR	CNN, Dense	2 –6	–
[17]	IMU, Temp, HR	Opportunity, Skoda, PAMAP2	LSTM, Ensemble	2 (x20)	–
[36]	Acc, Gyro, HR	PAMAP2	CNN, Dense	4	1M - 7M
[44]	IMU	Own (ADL)	CNN	1-4	–
[35]	IMU	Opportunity, Skoda	CNN, LSTM	8	986K
[22]	Acc, Gyro	HASC [24], UCI HAR	LSTM	1-4	–
[23]	Acc	UCI HAR , USC [56], SHO [46]	CNN	1-5	–
[52]	IMU	Opportunity, Hand Gesture [6]	CNN, Pool	3	–

Table 1: A summary of deep learning approaches to HAR from the last five years, including sensor modalities and architecture components used, the number of layers, and the total number of parameters (if disclosed) - selected to give a representative sample of architecture decisions in the literature. Key: N_L = No. of Layers, N_P = No. of Parameters, Acc = Accelerometer, Gyro = Gyroscope, IMU = Inertial Measurement Unit, CNN = Convolutional layer, Pool = Max or avg. pooling layer, LSTM = Long Short Term Memory layer, Bi-LSTM = Bidirectional LSTM, MLP = Multi-Layer Perceptron, AE = Auto Encoder.

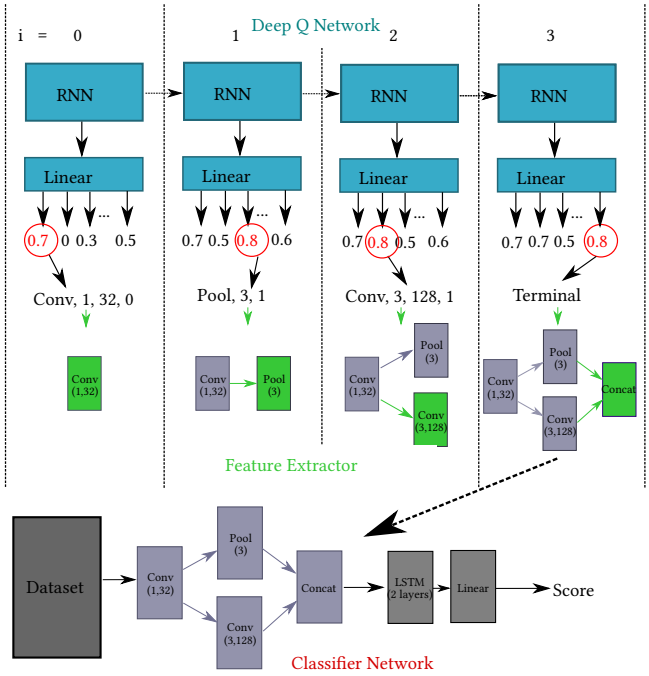

Figure 1: Block diagram which describes how we construct the classifier networks using the DQN. The top part shows the actions taken by the DQN to insert layers into the feature extractor. Here actions are selected with a greedy policy (i.e. $\epsilon = 0$), where the actions with the largest Q-values are selected at each index (circled in red). The network selects the action (Conv, 1, 32, 0), i.e. a convolutional layer with 32 kernels of size 1 connected to the input layer at $i = 0$. At $i = 1$, the DQN generates a pooling layer with a width of 3 samples connected to the first conv layer, denoted as (Pool, 3, 1). At $i = 3$, the DQN inserts another convolutional layer with 128 kernels of size 3 connected to index 1, and then finally the DQN generates a 'terminal' layer at $i = 4$. This indicates the completion of the feature extractor, which is included in the classifier network. Once constructed, the network is trained and tested on the target dataset, to produce a reward which is then used to train the DQN.

perform well on their respective datasets, but it is not clear whether they represent the best possible architectures, and which architectural parameters have the largest impact on this performance. An effective NAS method for wearable HAR should therefore be able to explore a search space which at least encompasses the majority of these networks, as well as novel architectures.

Under the RL paradigm for NAS, introduced in [58], a *controller* network (typically an RNN) is trained to generate suitable *classifier* architectures, which are then trained and evaluated on a target dataset to give feedback used to train the *controller* to generate better *classifiers* (see section 3.1). This method was used to generate competitive convolutional models for image recognition on CIFAR-10. To reduce the computational burden of training many network architectures, strategies have been proposed to predict converged performance from early validation epochs [4, 14, 57]. The approach used in this paper is closely related to BlockQNN [57].

Recently, NAS methods have also been applied to image-based and skeleton-based activity recognition [40, 55], as well as domain-agnostic time-series classification [41], with promising results. This work represents the first exploration of NAS with performance prediction for wearable sensor-based HAR.

3 Methodology and Experimental Setup

3.1 Deep Q Learning for NAS

A feature extractor is incrementally built by a series of actions performed at each time step. Each action corresponds to adding a layer chosen from 241 options, including convolutional layers (with kernel size in {1,2,3,5,8} and number of kernels in {32,64,128,256}), max pooling layers (with pooling size in {2,3,5}), concatenation of any two previous layers, and the terminal layer.

3.1.1 Search Spaces We define two search spaces, one *general* search space where a pooling or convolutional layer may be connected to any previously generated layer, allowing for arbitrary skip connections and branches (1.06×10^{16} architectures), and a restricted *feedforward* space which only allows for feedforward networks (8.17×10^{10} architectures), with no concatenations. Many networks of table 1 can be represented within these search spaces.

3.1.2 Controller Network Architecture We use two RNN layers with 64 units and a linear output layer with 241 units to learn the correlations between layer choices at each timestep and the complete *classifier* performance (in terms of weighted F1 score), with deep Q learning [34]. The value of each output unit is the expected *classifier* performance when its associated layer is chosen.

3.1.3 Search Policy To balance exploration of the search space with exploitation of the learned correlations between layer choices and *classifier* performance, an ϵ-greedy policy is used to choose the layer with the largest value with probability $1 - \epsilon$ and a random layer with probability ϵ. ϵ is decayed during training from 1 to 0.01.

3.1.4 Building the Feature Extractor At each RNN timestep t, we sample layers from the search space by feeding the DQN the layer index i_t and choosing a layer according to the ϵ-greedy policy. If the layer chosen is valid, we increment i and choose another layer, repeating until $i = 8$, or until the DQN chooses the terminal layer.

3.1.5 Classifier Generation, Training and Testing To evaluate the feature extractor, we combine it with a two layer LSTM recurrent network with 128 units per layer and a single linear classification layer with softmax output. This is almost identical to the output structure of DeepConvLSTM (we do not use dropout).

We train and validate the *classifiers* on the Opportunity dataset [15], which consists of 6 annotated runs from 4 subjects performing

18 sporadic gestures such as drinking water and opening doors. We use all 113 sensor channels. We split the dataset into a training set and a validation set, consisting of one run from user 1, and we hold out two runs from users 2 and 3 for testing (as in the Opportunity challenge [7]). Testing is performed on selected networks after the search to prevent overfitting to the test set. We use a sliding window size of 500ms (16 samples, twice the maximum kernel length).

This evaluation gives us the reward for the episode R_T, where T is the number of layers in the feature extractor. We allocate this reward evenly over each valid layer, setting the reward for each valid layer i to be $R_i = \frac{R_T}{T}$. Invalid layers receive a reward of -1.

3.1.6 Training the DQN with Experience Replay We train the DQN by sampling batches of 64 past experiences (corresponding to individual layers generated in past episodes). We train DQN according to the mean over the batch of the smooth L1 loss [16].

3.2 Converged Performance Estimation

In order to minimise computation time, we employ neural regression networks to approximate the true reward after training the classifier models for only a few epochs. As well as the training and validation statistics, we incorporate information about the structure of the classifiers and their computational complexity (approximated by the number of Floating Point Operations (FLOPs) per inference). We propose four prediction methods:

- *MLP*: A three layer perceptron with 64 units per layer, which takes as input the training loss and the validation loss, accuracy, class weighted F1 score and macro (sample weighted) F1 score at every training epoch, as well as the density (number of connections between layers divided by number of layers) and number of FLOPs of the subject.
- *CNN*: A branched convolutional network with a core structure the same as above, and an additional convolutional input layer with 64 kernels of size three which takes the training and validation statistics as a time-series input, and incorporates the density and number of FLOPs at the second layer.
- *MLP (struct)*: A variant of the MLP which additionally takes a vector representation of the network structure as input.
- *CNN (struct)*: A variant of the CNN which takes a vector representation of the network structure as an input.

We compare these methods against a *baseline* method which simply uses the mean validation F1 score over the 5 latest epochs (i.e. epochs 5-10 if training for 10 epochs) as the reward.

We generated, trained to convergence and tested 5000 randomly sampled networks from each of the general and feedforward search spaces, collecting training and validation statistics to produce two *databases* of models. The distribution of scores within each model database are shown in figure 2. We trained the predictors to minimise the MSE loss between predicted and actual testing F1 score, and we weighted the loss function according to the testing F1 score since we are chiefly interested in the best performing models. To assess the performance of the predictors, we performed a 10-fold cross-validation experiment on each database of models.

4 Results

Performance Prediction To analyse the results, we split the dataset into 5 bins based on their testing F1 scores. The rank correlations achieved by each predictive model on each partition of data are shown in the top part of figure 3. All of our prediction methods achieve better overall correlations than the baseline, and in addition they all achieve significantly better correlations in the high performance group (top 20% of networks), indicating that they are able to distinguish between high performing networks in early training epochs much better than the baseline. The best performing predictor at 5 epochs is the MLP, with a correlation of 0.54 on the top 20% of models compared to a baseline correlation of 0.17.

From the bottom sections of figure 3, we can see that there is a significant positive correlation between the testing performance of the classifiers we looked at and their computational complexity (the top 20% have over double the average FLOPs of the bottom 20%) and number of layers (from $\approx$ 4 to $\approx$ 6). We also observe a more modest increase in the node density and inference time of high performing classifiers, indicating deep networks with a few branches perform the best.

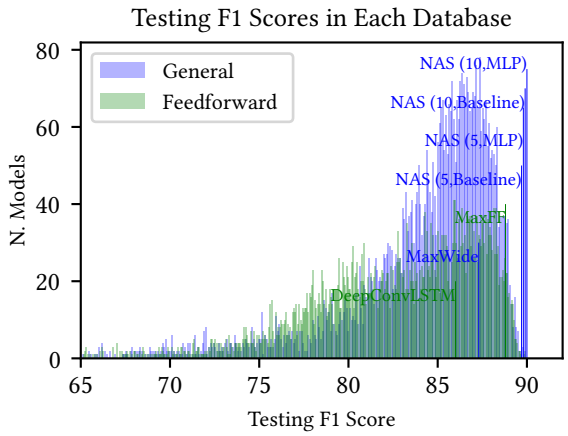

Figure 2: Density plot of testing F1 scores from 5000 randomly generated networks within the general and feedforward search space, annotated with F1 scores from benchmark models. The y-axis represents the number of models in each bin (where each bin is 0.01% F1 score) Blue or green text indicates that these models are contained within the general or feedforward search space, respectively. 'NAS (x,y)' refers to the best model found by NAS, when using x epochs and y method to predict scores. Other vertical lines represent models which we have implemented, trained and tested using the protocol described in section 3.1.5 as references.

Model	F1 [%]	Macro F1 [%]	Accuracy [%]	N_F	T_i [s]	T_s [hrs]
DeepConvLSTM	86.0 ± 0.5	56.0 ± 2.0	84.3 ± 0.6	5.3M	0.938 ± 0.001	N/A
MaxFF	88.8 ± 0.3	60.4 ± 1.2	88.2 ± 0.5	44.4M	1.885 ± 0.003	N/A
MaxWide	87.3 ± 0.2	57.8 ± 0.5	85.9 ± 0.3	38.6M	1.849 ± 0.005	N/A
NAS (Baseline, 5)	89.7 ± 0.1	62.7 ± 0.6	89.4 ± 0.2	19.4M	1.356 ± 0.046	≈ 5
NAS (Baseline, 10)	89.9 ± 0.2	61.9 ± 0.2	**89.7 ± 0.2**	22.5M	1.342 ± 0.028	≈ 10
NAS (MLP, 5)	89.8 ± 0.4	62.7 ± 1.1	**89.7 ± 0.4**	34.6M	1.499 ± 0.025	≈ 5
NAS (MLP, 10)	**90.0 ± 0.1**	**62.8 ± 0.6**	**89.7 ± 0.6**	47.2M	1.673 ± 0.002	≈ 10
RS (FeedForward)	89.6 ± 0.2	61.7 ± 0.7	89.5 ± 0.3	21.9M	1.295 ± 0.002	≈ 120
RS (General)	89.4 ± 0.3	61.1 ± 1.6	89.3 ± 0.2	17.0M	1.251 ± 0.004	≈ 120

Table 2: Weighted F1 score, macro F1 score and accuracy score achieved by various architectures. Also given are the number of FLOPs N_F per batch, inference time T_i and search time T_s (here the inference time is measured as the time taken to classify the whole testing set of 14,838 windows). All results obtained on a single RTX 2080 GPU. Performance obtained by training the model to convergence 5 times - the table shows mean +/- standard deviation. NAS (x, y) refers to the best model found during the search process using predictor x for y epochs. RS (Random Search) models represent the best models found generating two databases of random models.

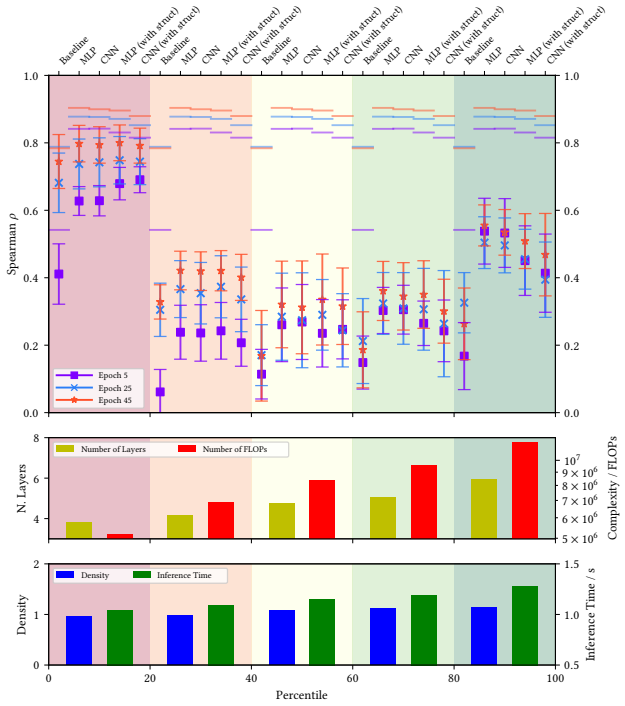

Figure 3: Fold-averaged (10-fold) spearman rank correlation coefficient with the converged F1 score achieved by various performance prediction methods on the general database when using data up to epoch 5, 25 and 45, split into groups by testing performance (from worst 20% of models on the left to best 20% on the right). Error bars represent the standard deviation over the folds. Overall correlation at each epoch is indicated by a horizontal line. The bottom two subplots show the average depth, complexity, graph density and inference time for each group of models within the general database.

Neural Architecture Search We performed four explorations of the search space, using the MLP and baseline prediction methods, and training the classifier models for 5 and 10 epochs. Table 2 shows the weighted F1 score, macro F1 score and accuracy of the best models found in each search run, as well as the inference time, number of FLOPs and time taken to search. Alongside these, we also present the same metrics for three benchmark models DeepConvLSTM, MaxFF and MaxWide, trained and tested under the same conditions as the NAS-generated architectures.

DeepConvLSTM refers to an implementation of the feature extractor part of a state-of-the-art model [37]. MaxFF refers to a feed-forward model with 8 convolutional layers, each with 256 kernels of size 5, while MaxWide refers to a model with 8 parallel convolutional layers with 256 kernels of size 5, thereby representing the deepest and widest limits of the search space.

From table 2, the NAS-generated models outperform the benchmark models on this task in all cases. The best feature extractor, shown in figure 4 was found using NAS with the MLP predictor, using 10 epochs of validation data. The best feature extractor has a large variety of convolutional kernel sizes, does not include any pooling layers, and uses a branched structure. The NAS generated models also have lower complexity than the two 'Max' benchmark models, but significantly higher complexity than DeepConvLSTM.

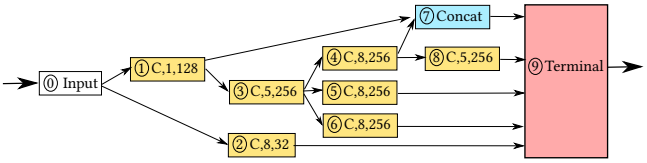

Figure 4: Best feature extractor generated by NAS with MLP performance predictor. C, x, y denotes a convolutional layer with y kernels of size x.

5 Discussion

While we have only applied our methods to one dataset, in principle the NAS and performance prediction methods are completely transferable to other datasets —all that would be necessary is to swap out the dataset in figure 1, and adapt the kernel and pooling sizes to suit the new dataset.

Although we find that our NAS method can generate better architectures than a random search in considerably less time, and that both produce networks which perform better than our implementation of DeepConvLSTM [37], this implementation performed significantly worse than reported in the literature [17, 18], and thus we were not able to show an improvement over the state-of-the-art F1 score. This highlights a problem also discussed in [14], namely that there are more factors than the architecture of a network which affect it's performance. This indicates a need for a common benchmark for NAS on HAR datasets, following the examples of [11] for CV and [25] for NLP, which would allow us to test NAS methods on a search space of pre-trained and pre-evaluated models.

Although our performance estimators achieve much better rank correlations than the baseline when predicting converged performance (see figure 3), this translated to only a marginally better searched feature extractor. This indicates that more work is needed to find better predictors which further improve the NAS results.

In this study we have chosen to search for the convolutional feature extractor part of a DeepConvLSTM-like network, in order to keep the size of the search space manageable for an initial characterisation. The method could in theory be applied to other search spaces including searching for recurrent cell structures.

6 Conclusions and Future Work

We have proposed a NAS method for designing convolutional feature extractors for Deep Recurrent Neural Networks using Deep Q Learning, and shown that our NAS-guided search was able to find feature extractor algorithms which beat our implementation of the state-of-the-art DeepConvLSTM by up to 4% F1 score on the Opportunity dataset, and which beat the naive maximum complexity algorithms we propose by 1-3% F1 score. We also achieved 0.4% better F1 score than the best model found in a random search, while reducing the search time by >90% through the use of a neural regression based performance estimator.

We found that our NAS-generated models were consistently larger and more complex than state-of-the-art models, indicating a need for future research focusing on reducing the complexity of solutions, for example using multi-objective RL. Future work could also include development of cross-dataset performance estimators taking into account other factors such as sample rate and gesture duration, and consideration of self-attention mechanisms [1].

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