# Accurate and Energy-Efficient Classification with Spiking Random Neural Network: Corrected and Expanded Version

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## Abstract

Artificial Neural Network (ANN) based techniques have dominated state-of-the-art results in most problems related to computer vision, audio recognition, and natural language processing in the past few years, resulting in strong industrial adoption from all leading technology companies worldwide. One of the major obstacles that have historically delayed large scale adoption of ANNs is the huge computational and power costs associated with training and testing (deploying) them. In the mean-time, Neuromorphic Computing platforms have recently achieved remarkable performance running more bio-realistic Spiking Neural Networks at high throughput and very low power consumption making them a natural alternative to ANNs. Here, we propose using the Random Neural Network (RNN), a spiking neural network with both theoretical and practical appealing properties, as a general purpose classifier that can match the classification power of ANNs on a number of tasks while enjoying all the features of a spiking neural network. This is demonstrated on a number of real-world classification datasets.

#### **Index Terms**

andom Neural Network; Spiking Neural Networks; Artificial Neural Network; Neuromorphic Computingandom Neural Network; Spiking Neural Networks; Artificial Neural Network; Neuromorphic ComputingR

#### I. Introduction

Despite being first proposed about 60 years ago [1], only in the past few years have artificial neural networks (ANNs) become the de facto standard machine learning model [2] achieving accurate state-of-the-art results for a wide range of problems ranging from image classification [3]–[5], object detection [6], [7], semantic segmentation [8], [9], face recognition [10], [11], and text recognition [12], [13], to speech recognition [14]–[16], natural language processing problems such as machine translation [17], [18], language modeling [19], and question answering [20]. This has resulted in a huge industry-wide adoption from leading technology companies such as Google, Facebook, Microsoft, IBM, Yahoo!, Twitter, Adobe, and a quickly growing number of start-ups.

One of the prominent reasons for this recent revival is that in order for ANNs to achieve such performance they need very large labeled datasets and huge computational power at a scale that only recently came into the hands of individual researchers in the form of GPUs [21], which kick-started the deep learning revolution in 2012 [3]. Since then, the trend for demanding more computation and more power consumption for such applications has largely increased.

Despite being initially bio-inspired architectures, ANNs have significant differences from actual biological neurons in how computations are performed by neurons, their structure (connection patterns and topologies of neurons), learning (how neurons adapt themselves to new observations), and communication (how inter-neuron data is encoded and passed).

One of the main differences of ANNs compared to biological neurons, is how communication is done. While biological neurons use asynchronous trains of spikes in an event-based, data-driven manner that adapts locally to its external stimulation pattern to communicate and encode data (though the specific encoding mechanism used by neurons is not totally understood), ANNs communicate in dense, continuous valued activations, which means that all ANN neurons are working at the same time, thus using lots of computation and energy to operate.

Spiking neural networks leverage the benefit from biological neurons to communicate asynchronously in trains of spikes. Thus, spiking neural networks incorporate the concept of time, and instead of all neurons firing at the same time as the case with ANNs, in spiking neural networks neurons fire only when thier intrinsic potential (i.e. membrane voltage) reaches a specific threshold [22], [23].

Neuroscientists have historically suggested several models for simulating how biological neurons communicate, and one of the simplest that is widely used is the integrate-and-fire (IF) model [24], in which the change in the membrane voltage  $v_{mem}$  is given by the equation:

$$\frac{dv_{mem}(t)}{dt} = \sum_{i} \sum_{s \in S_i} w_i \delta(t - s) \tag{1}$$

where  $w_i$  is the weight of the *i*th incoming synapse,  $\delta(.)$  is the Dirac delta function, and  $S_i = t_i^0, t_i^1, ...$  contains the spike times of the *i*th presynaptic neuron. If the membrane voltage crosses the spiking threshold  $v_{thr}$ , a spike is generated and the membrane voltage is reset to a reset potential  $v_{res}$  [25]. Several other models have also been proposed, such as te spike response model (SRM) [26], and the Izhikevich model [27].

One of the prominent differences between spiking neural networks and ANNs is how they learn and adapt to new signals. ANNs have been predominantly trained in the literature using Backpropagation [28], and with variants of stochastic gradient descent (SGD), which can summarised as moving the vector of network parameters or weights  $\theta$  in the direction of the negative gradient of some loss function that characterizes the deviation network's current output from the ground truth labels of input data.

Training spiking neural networks on the other hand is still an open research issue with many proposed solutions and no consensus [29]. One of the most popular and biologically plausible learning methods in spiking neural networks is unsupervised learning using Spike Timing Dependent Plasticity (STDP) [30], [31], in which the synaptic weight is adjusted in accordance with the relative spike times of the presynaptic and postsynaptic neurons.

An important problem that has always faced using the popular gradient-based optimization algorithms in spiking neural networks is that both spike trains and the underlying membrane voltage are not differentiable at the time of spikes,. Thus researchers tried different approaches to alleviate this problem, and one of the most successful has been the workaround of first training an ANN and then converting it to a corresponding spiking neural network [25], [32], [33].

Though von Neumann architectures [34] work very well to run ANNs, it was suggested as early as the 1980s that they were not adequate for running the more realistic spiking neural networks models efficiently, and a new architecture was needed to realize thier power and computational efficiency [35]. The recent success of ANNs has pushed this trend much faster.

The main idea behind Neuromorphic Computing was to design Integrated Circuits (ICs) that are arranged and behave like living neurons (i.e. to mimic how the brain performs computation) [36], and spiking neural network models of bioglogical neurons have historically been used as a guiding design in this process. After years of attempts, the past few years saw the demonstration of Neuromorphic Computing platforms with millions of neurons while requiring only milliWatts of power for thier operation such as TrueNorth [37], SpiNNaker [38], and Loihi [39]. A number of pattern classification applications were demonstrated to run efficiently and accurately on such chips while being orders of magnitude more efficient in terms of power consumption than an ANN on a von Neumann CPU or GPU running a similar task.

The main source of this power saving is the asynchronous working and firing of spiking neural networks described earlier, so neurons fire and the chip consumes power only when needed, which is completely different than what happens in an ANN when all neurons are obliged to fire synchronously leading to unnecessary computation and energy consumption. This efficiency can be even increased when using input from neuromorphic sensors such as silicon retinas [40] or cochleas [41], which create sparse, frame-free, and precisely timed trains of signals, with substantially reduced latencies compared to traditional frame-based approaches which produce large volumes of redundant data and therefore consume much power. This line of neuromorphic sensor design has been applied to vision sensors, auditory sensors, and olfactory sensors [42].

This paper presents results that show how a spiking model known as the Random Neural Network (RNN) [43] can be used effectively and efficiently for Machine Learning applications, resulting in a level of performance comparable to the best ANN results.

The rest of the paper is structured as follows: The Random Neural Network is described and reviewed in Section II; our experimental setup is described and results presented in Section III; the conclusions and future work are drawn in Section IV

## II. THE RANDOM NEURAL NETWORK (RNN)

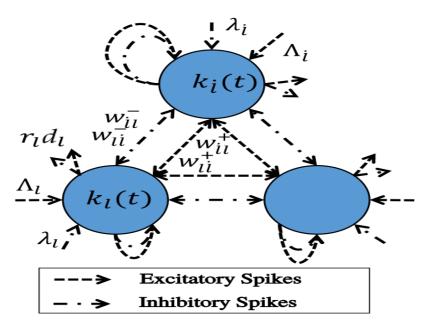


Fig. 1. Schematic representation of a Random Neural Network (RNN).

The Random Neural Network (RNN) [43]–[45] has a powerful property of approximating continuous and bounded real-valued functions [46]. This property serves as the foundation for RNN based learning algorithms, both for recurrent (containing feedback) and feedforward networks [47], and for Deep Learning [48], [49].

The RNN has been used for modelling natural neuronal networks [50], and for protein alignment [51]. It has been used in several image processing applications including the accurate evaluation of tumors from brain MRI scans [52] and the compression of still and moving images [53]–[55]. It was recently introduced as a tool for predicting the toxicity of chemical compounds [56].

In the field of computer networks, the RNN has been used to build distributed controllers for quality of service routing in packet networks [57]–[59] and in the design of Software Defined Network controllers for the Internet [60], [61]. Real-time optimised task allocation algorithms in Cloud systems [62] have also been built and tested. Recent applications has addressed the use of the RNN to detect network attacks [63] and attacks on Internet of Things (IoT) gateways [64].

On the other hand, G-Networks [65] are a family of queueing networks that generalize the RNN model, and like the RNN they have a convenient and computationally efficient "product form "mathematical solution. The computation of the state of a G-Network is obtained via a simple fixed-point iteration, and the existence and uniqueness of the solution to the key G-Network state equation is shown in [66]. G-Networks incorporate useful primitives, such as the transfer of jobs between servers or the removal of batches of jobs from excessively busy servers, that were developed in a series of successive papers [67]–[70]. They have a wealth of diverse applications as a tool to analyse and optimise the effects of dynamic load balancing in large scale networks and distributed computer systems [71]. They are also used to model Gene Regulatory Networks [72], [73]. A recent application of G-Networks is to the modelling of systems which operate with intermittent sources of energy, known as Energy Packet Networks [74]–[78].

## A. The RNN as a Mathematical Model

Figure 1 gives a schematic diagram of a RNN for a system with L neurons. The state of neuron i at time t is represented by a non-negative integer called its potential, denoted by  $k_i(t) \geq 0$ . Network state at time t is a vector  $k(t) = (k_1(t), \ldots, k_i(t), \ldots, k_L(t))$ . When an excitation spike arrives to neuron l, the state of neuron i is changed from  $k_i(t)$  to  $k_i(t) + 1$ . When an inhibition spike arrives to neuron i, its state from  $k_i(t)$  to  $k_i(t) - 1$  if  $k_i(t) > 0$ , and does not change if  $k_i(t) = 0$ .

Each neuron i receives exogenous or external excitation spikes in the form of two independent Poisson processes of rates  $\Lambda_i \geq 0$  and  $\lambda_i \geq 0$ , respectively. These represent the external inputs to the network.

Neuron i can emit a spike if  $k_i(t)$  is positive (i.e. it is excited); this occurs with probability  $r_i\Delta(t) + o(\Delta(t))$ , where  $r_i \ge 0$  is the "firing rate" of neuron i. Ehen this happens, neuron i's state changes from  $k_i(t)$  to  $k_i(t) - 1$ . The spikes are then sent.

Spikes are sent from the outside world to neuron i as a positive signal according to Poisson processes of rate  $\Lambda_l$  or as a negative signal according also to Poisson processes of rate  $\lambda_l$ 

Each spike is sent out from neuron i to neuron j as a positive or excitatory spike with probability  $p_{ij}^+$ , or as a negative or inhibitory spike spike with probability  $p_{ij}^-$ , or it departs from the network with probability  $d_i$  which represents the probability that spikes emanating from a neuron may be "lost" for a variety of reasons, and does not reach any target neuron j. The sum of these probabilities must be one:

$$d_i + \sum_{j=1}^{L} [p_{ij}^+ + p_{ij}^-] = 1, \forall i .$$
 (2)

The spikes are sent out from neuron i to neuron j at rates:

$$w_{ij}^+ = r_i p_{ij}^+ \ge 0, \ w_{ij}^- = r_l i \ p_{ij}^- \ge 0,$$
 (3)

and  $w_{ij}^+$  and  $w_{ij}^-$  are called the excitatory and inhibitory weights, respectively.

Combining equations (2) and (3) we get:

$$r_i = \frac{\sum_{j=1}^{L} [w_{ij}^+ + w_{ij}^-]}{1 - d_i} \ . \tag{4}$$

Let  $q_i = \lim_{t \to \infty} Prob(k_lit) > 0$ ) denote the stationary excitation probability of neuron i. The total arrival rates of positive signals  $\Omega_i$  and negative signals  $\Omega_i^-$ , for  $i = 1, \dots, L$ , can be calculated from the following nonlinear system of equations:

$$\Omega_i^+ = \Lambda_i + \sum_{j=1}^L q_i w_{ij}^+, \ \Omega_i^- = \lambda_i + \sum_{j=1}^L q_i w_{ij}^-$$
 (5)

It has been proven that the  $q_i$  can be directly calculated by the following system of equations:

$$q_i = \min\left\{1, \frac{\Omega_i^+}{r_i + \Omega_i^-}\right\}, \ 1 \le i \le L, \tag{6}$$

and furthermore that if all the resulting  $q_i$  are strictly less than one, then:

$$Prob[k_1(t) = k_1, \dots, k_L(t) = k_L] = \prod_{i=1}^L q_i^{k_i} (1 - q_i),$$
 (7)

which is known as a "Product Form Solution".

The existence of a solution to the system of L non-linear equations (6) and the uniqueness of the solution has been proven [47]. Therefore, the states of the RNN can be obtained by solving (6), for instance using a fixed-point iteration.

#### III. EXPERIMENTAL RESULTS USING THE RNN

We know that spiking neural network-based RNNs are empirically at least as powerful as ANNs in this category of classification problems. It was already shown that RNNs are universal function approximators for continuous and bounded functions [79], [80], and hence as computationally capable as multi-layer perceptrons in this respect [81]. However, RNNs have been shown to have an unique solution even in the recurrent case [47], [55], [82], and furthermore in the recurrent case the RNN's learning algorithm is still of low polynomial time and space complexity [83]–[85].

Here we will provide experimental results on a number of benchmark real world classification datasets that are widely used in the literature. These experimental results can be reproduced using the software and and data stored at the web site www.github.com/ASDen/Random\_Neural\_Network.

Another web site that specializes in Deep Learning with the Random Neural Network can be found at https://github.com/yinyongh/DenseRandomNet.

## A. Evaluation Setup

Dataset	# Attributes	# Features	# Output Classes
Iris	4	150	3
Breast Cancer Wisconsin	9	699	2
Glass	9	214	7
Ovarian cancer	100	216	2

TABLE I

NAMES AND STATISTICS OF THE DATASETS THAT ARE USED.

Table VI shows statistics about the used datasets. We use the Iris, Breast Cancer, and Glass datasets from the UCI machine learning repository [86] and the Ovarian cancer dataset [87]. We train the RNN using the procedure described in [88] based on [89]; the related software and data sets are at www.github.com/ASDen/Random\_Neural\_Network. The algorithm can be summarized as follows: leftmargin=\*,labelsep=4.9mm

- 1) Assume the given dataset has K pairs of input training patterns for an  $L-vector\ x_k=(x_{1l},\ ...\ ,x_{Lk})$  associated with the output value  $L-vector\ y_k=(y_{1l},\ ...\ ,y_{Lk}).$ 2) Initialize the weights  $w_{ij}^+$  and  $w_{ij}^-$ ,  $\forall (i,\ j)$ , to random values between zero and one. 3) Set the external inhibitory arrival rates to zero.

- 4) Set the external excitatory input rates for the input neurons,  $\Lambda_k = x_k$ , where  $x_k$  is the kth input training pattern.
- 5) Solve the nonlinear system of equations (6) to obtain each neuron's stationary excitation probability  $q_i, \forall i$ .
- 6) For all the given (input, output) values  $(x_k, y_k)$ , iterate through the RNN recurrent network learning algorithm [89], [90] till convergence, updating at each step the weights  $w_{ij}^+$  and  $w_{ij}^-$ ,  $\forall (i, j)$ , so as to minimize the following error function:

$$E = \sum_{k=1}^{K} \sum_{i=1}^{L} [q_{ik} - y_{ik}]^2$$
 (8)

# B. Dataset Description

Here we give a brief description of the four datasets used for evaluation: leftmargin=\*,labelsep=4.9mm

- 1) Iris dataset [86]: Each instance is described by four plants attributes (sepal length and width, and petal length and width) all are real numbers and the task is to recognize which class of Iris plants (Iris Setosa, Iris Versicolour, or Iris Virginica) a given test instance belongs to.
- 2) Breast Cancer Wisconsin dataset [86]: Each instance is described by 9 numerical attributes, that range from 1 to 10. The attributes include the clump thickness, uniformity of cell size, uniformity of cell shape, marginal adhesion, single epithelial cell size, bare nuclei, bland chromatin, normal nucleoli and mitoses. This breast cancer databases was obtained from the University of Wisconsin Hospitals, Madison from Dr. William H. Wolberg. The task is to recognize the class of the beast cancer (benign or malignant).
- 3) Glass dataset [86]: Each instance has 9 continuous attributes, including the refractive index and the unit measurements of sodium, magnesium, aluminum, silicon, potassium, calcium, barium and iron. There are in total 7 types of glass, while there are instances of only 6 types of glass in the dataset. The task is to using the 9 attributes to recognize which type of glass this instance belongs to (whether it is windows glass or non-window glass).
- 4) Ovarian Cancer dataset [87]: From the FDA-NCI Clinical Proteomics Program Databank, the dataset comprises 216 patients, out of which 121 are ovarian cancer patients and 95 are normal patients. Each instance has 100 attributes, each of which represents the ion intensity level at a specific mass-charge value. The task is to recognize the class of the ovarian cancer (benign or malignant).

# C. Results

Tables II, III, IV, and V display confusion matrices of RNN on the four datasets. Table VI compares the accuracy of RNNs against ANNs some UCI datasets. For the ANN results, we use results obtained on UCI datasets from the comprehensive study in [91]. We can clearly see in VI that RNNs are at least as powerful as ANNs in these datasets and can deliver excellent classification accuracy.

Class	Setosa	Versicolour	Virginica
Setosa	1.0	0.0	0.0
Versicolour	0.0	1.0	0.0
Virginica	0.0	0.0	1.0

TABLE II

CONFUSION MATRIX FOR IRIS DATASET.

Class	Positive	Negative
Postivie	0.984	0.016
Negative	0.067	0.933

TABLE III

CONFUSION MATRIX FOR BREAST CANCER DATASET.

Class	Positive	Negative
Postivie	1.0	0.0
Negative	0.127	0.8139

TABLE IV

CONFUSION MATRIX FOR GLASS DATASET.

Class	Postive	Negative
Postive	1.0	0.0
Negative	0.1064	0.8936

TABLE V

CONFUSION MATRIX FOR OVARIAN CANCER DATASET.

Dataset	RNN	ANN
Iris	1.0	0.959
Breast Cancer Wisconsin	0.964	0.963

TABLE VI

ACCURACY COMPARISON BETWEEN RNN, AND ANN. BEST RESULT IN EACH DATASET IS IN BOLD.

#### IV. CONCLUSIONS

In this paper, we have motivated the need for power and computation efficiency in neuromorphic models that are used in Machine Learning, and discussed some of the shortcomings of current ANN models in this respect. We have briefly presented and reviewed some spiking neural networkmodels used for neuromorphic computing as a possible alternative due to their low power usage and computational efficiency, but we have also indicated their limitations with regard to being harder to train and their generalization performance.

We have then presented a specific spiking neural network model, the Random Neural Network (RNN) that was first introduced in [92]. We have indicated that the RNN's special analytical properties makes it much easier to train, and we have shown empirically that it provides a generalization performance that is at least as powerful as conventional ANNs for a number of real world classification datasets, while achieving the efficiency associated with spiking neural networks.

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