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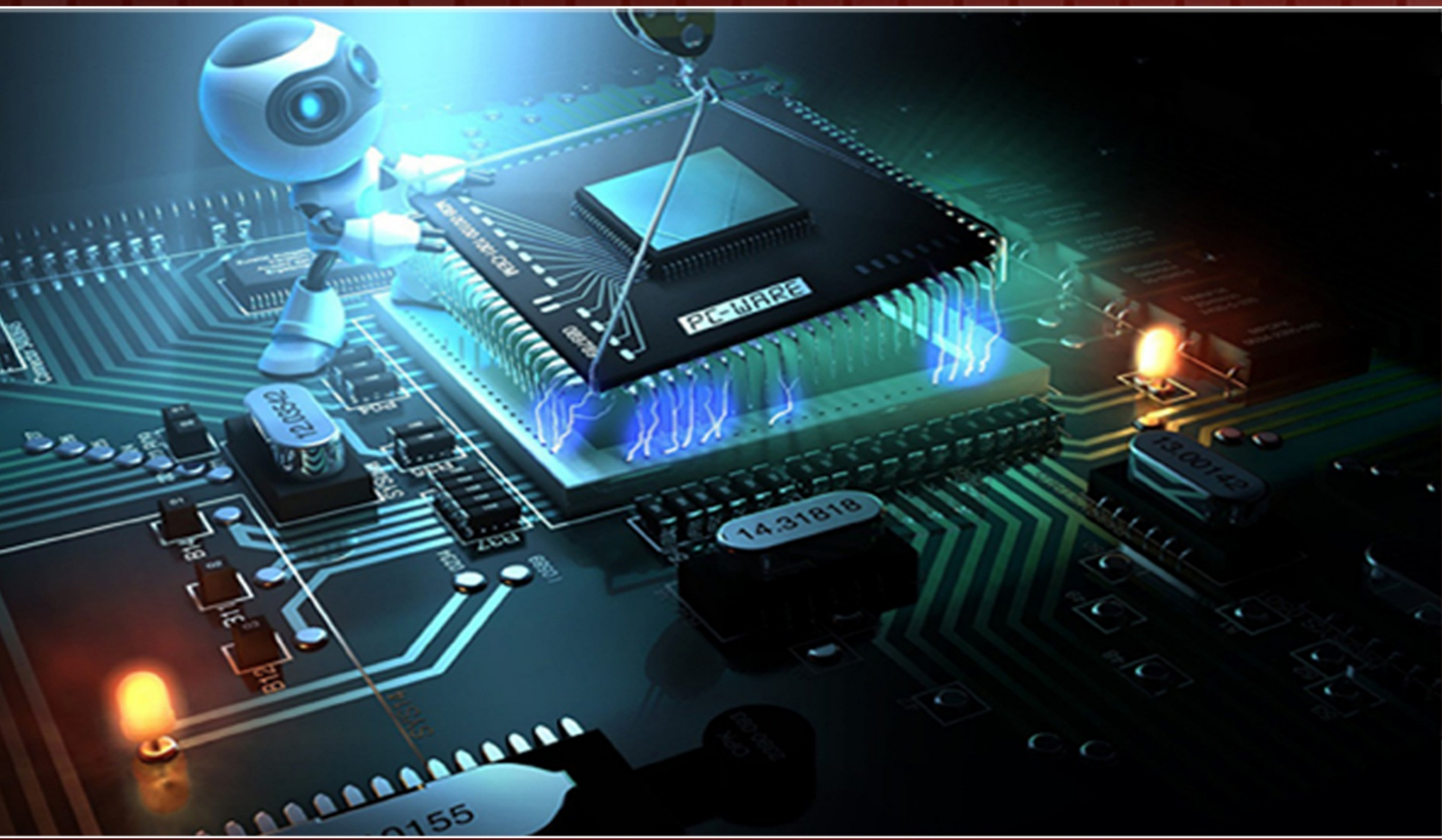

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TABLE OF CONTENTS

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Fall Detection System based on BiLSTM Neural Network

[1]Biao Ye, [2]Lasheng Yu
[1,2] *School of Computer science and Technology, Central South University, Changsha, Hunan, China;*
404871394@qq.com;yulasheng@csu.edu.cn

ABSTRACT

The purpose of this article is to analyze the characteristics of human fall behavior to design a fall detection system. The existing fall detection algorithms have problems such as poor adaptability, single function and difficulty in processing large data and strong randomness. Therefore, a long-term and short-term memory recurrent neural network is used to improve the effect of falling behavior detection by exploring the internal correlation between sensor data. Firstly, the serialization representation method of sensor data, training data and detection input data is designed. The BiLSTM network has the characteristics of strong ability to sequence modeling and it is used to reduce the dimension of the data required by the fall detection model. then, the BiLSTM training algorithm for fall detection and the BiLSTM-based fall detection algorithm convert the fall detection into the classification problem of the input sequence; finally, the BiLSTM-based fall detection system was implemented on the TensorFlow platform. The detection and analysis of system were carried out using a bionic experiment data set which mimics a fall. The experimental results verify that the system can effectively improve the accuracy of fall detection to 90.47%. At the same time, it can effectively detect the behavior of Near-falling, and help to take corresponding protective measures.

Keywords: BiLSTM neural network, fall detection; near-falling detection; sensor data

1 Introduction

With the advent of the ageing population, the number of old people who is living alone has also increased. As the age of the elderly increases, the muscle strength, balance, and responsiveness of the body gradually decline [1], which has increased the probability of falling behavior. Falling behavior is especially serious the lives and property of the elderly. It is very important to make timely warnings about possible fall behaviors, so as to reduce and avoid the harm caused. Current research at our country and other countries mainly includes: The old fall detection system based on ZigBee IoT technology[2]. Visual-based fall detection system [3], and Wearable device-based fall detection system and other types.

Among them, the old man's fall detection which utilizing Zigbee technology in the Internet of Things is too single function, the use conditions are limited, and the visual fall detection involves the user's privacy and the camera can't be carried around, so the fall detection system based on the wearable device is easy to use and low in cost and become the current research hotspot.

The two most common sensors are the tilt angle sensors and the acceleration sensors. With the development of the gait recognition system, the behavior parameters of foot pressure are also applied to fall detection[4]. The foot pressure is measured by the force plate to measure the reaction force of the

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ground during walking. This paper synthesizes the changes of behavioral characteristics such as human body acceleration, tilt angle and foot pressure during daily activities and fall behaviors of human body. A fall detection algorithm combining multiple behavioral characteristics is proposed.

The threshold method is a commonly used fall detection algorithm. By setting one or more thresholds, the information such as acceleration and angular velocity acquired by the wearable device sensor is classified, and the main advantages are lower time and space complexity**Error! Reference source not found.**. However, the threshold is mostly determined by experimental or empirical methods. The size of the threshold directly affects the recognition of the fall behavior, and there are problems such as poor applicability to different individuals.

As researchers deepen their focus on fall algorithms, they began to study hidden Markov chains[6], dynamic naive Bayesian networks[8], support vector machines [9], Multi-weight neural network [9], and k nearest neighbors[11]. All of above based on the pattern recognition method applied to fall detection, these methods abstract the model data collected by the sensor for the classification of fall behavior, and have strong adaptability. However, only the sensor is used to obtain a single acceleration or some features for detection, lack of human behavior parameters, and there are problems such as insufficient precision, and the near-fall state with high use value is not distinguished. The neural network model has self-learning function, high-speed search for optimal solution, and association storage function compared with the traditional model. The neural network model can acquire a large amount of data through sensors to train, learn and mine the internal structural features of the data, and improve the adaptability and accuracy of the classification system. Relative to Convolution neural network spatially through the sliding window to store part of the historical input, Cyclic neural network can retain the previous input in time due to the inter-connected features of its hidden layers, by abstracting the association between the previous inputs, with a certain classification accuracy. However, since the previous input is continuously updated during the delivery process, the information retention rate is very low. LSTM joins the state in the hidden layer to support the defect of RNN, and solves the problem of gradient fading that is easy to appear in RNN.

At present, LSTM has been successfully used in language translation, image analysis, robot control, disease prediction and other fields.

This paper mainly introduces BiLSTM into the fall detection system. The main work arrangements are as follows:

(1) Firstly, the human behavior is classified, and analyzed the changes of the human body's gravity acceleration, angular acceleration and pressure division of the foot are analyzed.
(2) According to the characteristics of LSTM, the data acquired by the sensor is serialized and converted into an input sequence suitable for model training.
(3) With LSTM, historical information can be preserved, and the intrinsic relationship between location and pressure sensor data can be fully exploited by using feature discovery and abstract sequence intrinsic relationship. An iterative algorithm based on LSTM is designed to improve the effect of fall detection.
(4) On the TensorFlow platform, the LSTM-based iterative algorithm is used to implement the LSTM-based fall detection system. In addition to distinguishing between normal and fall behaviors, the existing fall detection system can accurately identify more dangerous. Close to the fall behavior.
(5) Obtain the sensor data on the experimenter's body through the bionic experiment, and use the data which has been pre-processed to train and test the fall detection model as the training and

test data set. Compared with other algorithms on the same data set, the BiLSTM-based fall detection system can achieve higher accuracy and correctly detect the near-fall behavior, so as to better protect the fall behavior.

2 Related Work

2.1 Fall Detection

Vaidehi and his team, from Anna University in India, proposed a fall detection method based on static human image features. Through using the camera to collect pictures of the human body standing, falling, climbing and other actions, and extract the two aspects of the aspect ratio and the tilt angle of the human body from the picture, and perform the fall detection according to the threshold method [12]. Bogdan Kwolek and Michal Kepski use the Kinect sensor, which sets the threshold of the acceleration signal and filters out the number of non-falling events. Finally, by collecting the depth map and acceleration information as the data set, the k-nn algorithm is used to classified falls and non-fall events[13]. L.Chen,et al. used Bayesian network to realize human body attitude prediction. The attitude prediction combined with recognition algorithm was used to improve the prediction time. Then, the support vector machine method was used for fall recognition. The recall rate and accuracy rate reached 96.2% and 87.3% respectively. [14] D. Luo et al. proposed a fall detection algorithm based on random forest, which finally achieved 95.2% accuracy, 90.6% sensitivity and 93.5% specificity, and compared with SVM and back propagation (BP) neural networks. The conclusion of the detection algorithm. The pressure sensor-based fall detection system researched by Shi Xin et al. of Chongqing University analyzes the difference between the sole pressure in different human states through the system **Error! Reference source not found.**.

3 model based on LSTM neural network

3.1 LSTM neural network principle

The LSTM neural network was first proposed by Hochreiter et al. [15], and then improved by Graves [17] is a kind of perfection based on RNN, which solves the problem of gradient extinction which is easy to appear in RNN. A single RNN hidden layer unit is shown in Figure 1.

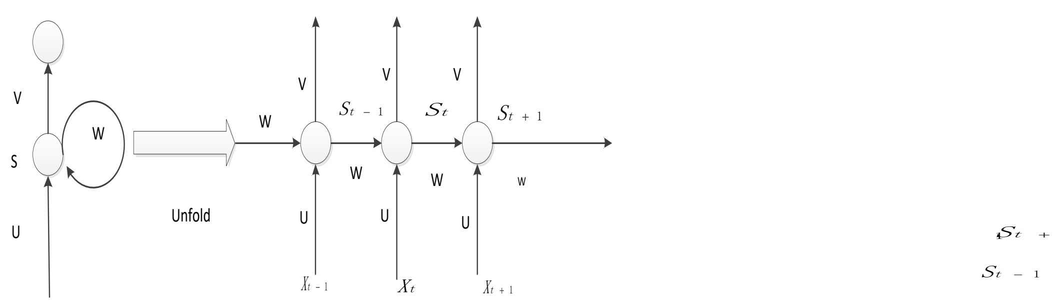

Figure 1: Single RNN neuron expansion diagram

As shown, U, V, and W are the input to the hidden layer, the hidden layer to the hidden layer, the hidden layer to the output weight, x is the input of the neural network, O is the output of the neural network, and S is the current state of the moment in the hidden layer. In traditional neural networks, the parameters of each network layer are unshared. In RNN, each step shares each parameter U, V, W. This reflects that every step in the RNN is doing the same thing, but the input is different. This training method greatly reduces the parameters that need to be learned in the network, and greatly shortens the training time under the premise of ensuring accuracy.

However, for the standard RNN architecture, the "context" that can be connected in practice is very limited, and the influence of "memory" at the far end on the output is either small or exponential. LSTM is an improved RNN for solving the phenomenon of gradient demise. LSTM unit is shown in Figure 2.

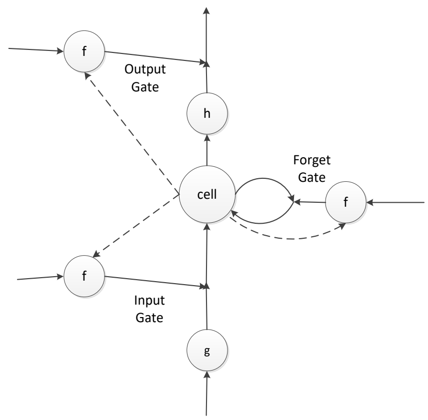

Figure 2: Single LSTM neuron

Algorithms implemented in LSTM neurons include:

$$i_t = \sigma(W_t x_t + U_i h_{t-1} + b_i) \qquad f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f)$$

$$\widetilde{c_t} = \tan h(W_c x_t + U_c h_{t-1} + b_c) \qquad c_t = f_t \odot c_{t-1} + i_t \odot \widetilde{c_t}$$

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o) \qquad h_t = o_t \odot \tan h\,(c_t)$$

Among them, x_t represents the input vector of time t, b represents the offset value， i_t represents the input gate which determines how much of the network input is retained to the cell state at the current time, f_t represents that the forgetting gate determines how much the state of the neural unit remains to the current state of the neural unit at the last moment , O_t represents the output gate, which controls how much the unit state has output to h_t， $\widetilde{c_t}$ is used to describe the current input neural unit status， C_t represent the state of the nerve unit at the current time , U and W represent weight matrix, $\tan h$ represents a hyperbolic tangent activation function that processes the input data to map it to the range [-1,1]， σ represents that the sigmoid function used on the three middle gates maps the input to [0,1]， h_t represents the output of the neural unit signal at time t.

In addition to the detection of the fall state and the non-fall state, the fall detection model in this paper adds a very research-worthy state close to the fall. The normal LSTM is a one-way neural network that can only be saved from the back and forth. The status information is transferred, and the relationship between the incoming state and the current state cannot be discovered. Therefore, this design uses BiLSTMs with opposite directions to fully exploit the relationship between two adjacent time state sequences. The structure is shown in Figure 3.

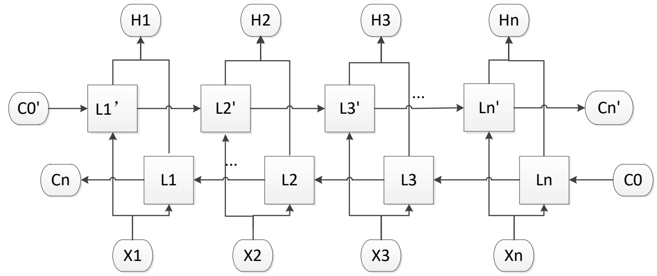

Figure 3: BiLSTM structure

As shown in the figure, in the forward transfer, the Cn of the hidden layer is related to Cn-1; in the reverse calculation, Cn is related to Cn+1:

$$Cn = f\left(U_1 x_n + W_1 c_{n-1}\right) \qquad C_n' = f(U_2 x_t + W_2 C_{n+1}')$$

$$O_t = g(V C_n + V' C_n')$$

3.2 Sensor data processing

3.2.1 Acquisition of acceleration and angular velocity

The module used for the combined acceleration and angular velocity acquisition required in this paper is the MPU6050, which has an integrated 6-axis motion processing component. The MPU6050 not only integrates a three-axis accelerometer and a three-axis gyroscope, In the MPU6050, the signals collected by accelerometers and gyroscopes are all implemented by three 16-bit analog-to-digital converters. The conversion outputs the result in digital form. To accurately track fast and slow motion, the sensor's measurement range is user-controllable. Among them, the range of the gyroscope can be divided into: ±250 ° / sec, ± 500 ° / sec, ± 10007 sec, ± 2000 ° / sec. Acceleration measurement range from small to large: ± 2g, ± 4g, ± 8g, ± 16g.

3.2.2 Acquisition of plantar pressure

When the movement of the human body changes, the pressure of the sole also sends a series of changes. The pressure insole used in this paper puts the pressure sensor in the insole and the shoe, and can measure the pressure of the sole in real time.

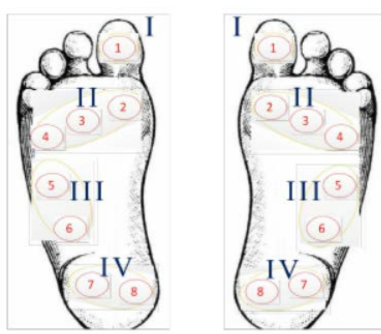

Figure 4: Two-leg pressure sensor distribution diagram

1 to 8 in Figure 4 are respectively equipped with a pressure sensor (Force Sensitive Resistor, FSR). The left and right feet (L for the left foot and R for the right foot) are divided into the same way, forming a symmetrical area in the plane. Region I have one FSR No. 1 and is located in the thumb; Region II has FSRs 2, 3, and 4 located in the plantar tibia; Region III has FSRs 5 and 6 on the lateral side of the foot; Region IV

has FSRs No. 7 and No. 8 Heel. According to the information of 150 sampling points collected by the plantar sensor, the voltage output value converted from the plantar pressure changes regularly during normal walking, and periodically changes from 0V to 3.3V.

3.2.3 Data serialization

When we only use $\vec{a} = \{a_x(t), a_y(t), a_z(t)\}$ to represent three axial acceleration data, the acceleration data of one axis alone is not enough to accurately determine the posture of the human body. Therefore, SMV (Signal Magnitude Vector) is introduced as a characteristic parameter to describe the motion state of the human body. this parameter can reflect the severity of human exercise very well.

Some documents also refer to it as signal vector mode (SVM) and can be divided into SMV_A $and.$ SMV_W . Among them, SMV_A represents the space triaxial acceleration vector sum, and some documents are also called the combined acceleration, and the calculation formula of the acceleration at a certain time t:

The formula for calculating the angular velocity at a certain time:

$$SMV_w = \sqrt{\omega_x^2(t) + \omega_y^2(t) + \omega_z^2(t)}$$

The rate of change of acceleration SMA indicates the speed of acceleration change, and also reflects the degree of action change. The calculation formula:

$$\mathrm{SMA} = \frac{1}{t}(\int_0^t |a_x(\mathrm{t})|\,\mathrm{d}t + \int_0^t |a_y(\mathrm{t})|\,\mathrm{d}t + \int_0^t |a_z(\mathrm{t})|\,\mathrm{d}t)$$

Combined acceleration rate MADS（mean absolute value of different SMV_A ）

It is an important parameter that distinguishes the state of motion of the human body. The calculation formula is:

$$MADS = \frac{1}{T}\int_0^T |SMV_A'|\,\mathrm{d}t$$

The human body tilt angle is defined as the human torso (Z-axis positive) and vertical upward

The angle between the calculation formula:

$$BTA = \arccos\left(\frac{a_2(t)}{g}\right) x \left(\frac{180}{\pi}\right)$$

The position sensor data sequence SS is defined, which includes three values of the SMA, SMV_A and BTA obtained by the gravity acceleration and angular acceleration, which converts the spatial position information collected by the position sensor into a data sequence， Then define the pressure wear sensor data sequence, PS1 contains the pressure values L1~L8 obtained by the left foot pressure sensor, PS2 contains R1~R8, then merge them and define the behavior training array AS (SS, PS1, PS2, action), action The type of current behavior, 0 means non-falling, 1 means falling.

LSTM can discover and abstract the relationship between each unit in the input sequence, and obtain the abstraction of the relationship between multiple position sensors, which provides a basis for improving the accuracy and adaptability of fall detection.

In AS, the 3 values in each SS included in the AS and the values of PS1, PS2, and action are used as independent input units, and then the independent input unit is used as the input of the input layer for the training of the LSTM for fall detection. The output layer calculates the current probability Pt of the behavior training sequence group and counts the total probability P of each AS as the basis for training and detection.

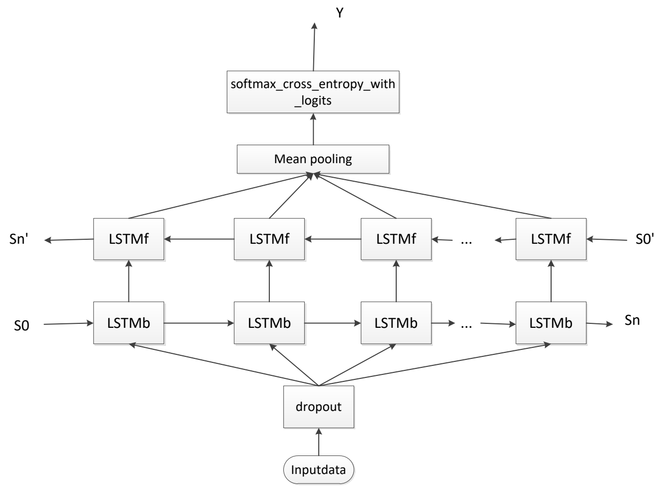

Figure5: Fall detection model

The TensorFlow flow chart of the research build is shown in Figure 5. in the model diagram, Input data represents an instance of a person's motion state at a certain moment, that is, a multivariate time series. The dropout operation randomly picks out the neural units that work together. The purpose is to prevent the model from being over-fitting, eliminating the weakening of the joint adaptability between the neuron nodes and enhancing the generalization ability. Next, the data is passed into two identically structured LSTMs, a forward input sequence, and an inverted input sequence, which combine the outputs of the two as the final result.

On the last layer of the BiLSTM neural network, the Mean Pooling mechanism can be used to fuse the result information of each node of the LSTM network. The weighted average of the output results is obtained by superimposing the output contents of the respective nodes of the BiLSTM and dividing by the number of input nodes. The weighted average of the output results is obtained by superimposing the output contents of the respective nodes of the BiLSTM and dividing by the number of input nodes. After the softmax activation function, the classification problem is transformed into a probability problem by mapping each output to a 0 to 1 interval.

The cross entropy loss function is used to calculate the error between the model output and the real category label.

The above is the BiLSTM-based fall detection model built using TensorFlow. The main training parameters of this model include the skew and weight between the input layer and the hidden layer, and the weights and offset values of the three gates in the LSTM neuron unit. After the loss function Loss is given, the training operation provided by TensorFlow can automatically find the differential derivative of Loss on each parameter and train the model by gradient descent method.

4 Experiment and Analysis

this experiment collected 8 females and 12 males in the 18-40 age group. For the 20 samples, the mean and variance of their age, height and weight were (26.2 ± 6.7) years, (165.2 ± 5.8) cm and (70.8 ± 15.1) kg, respectively.

The action of the specific experiment is shown in Table 5.1

Table 5.1 Action in the Simulation experiment

Action	Category	Number of experiments
Walk	Non-falling behavior	10 times / person
Bend over	Non-falling behavior	
Underarm	Non-falling behavior	
Stand up	Non-falling behavior	
Lean forward	Near-fall behavior	
Tilt back	Near-fall behavior	
Dump forward	Fall behavior	
Dump backwards	Fall behavior	
Slip to the left	Fall behavior	
Slip to the right	Fall behavior	

According to the information in the above table, the experimenter simulates the three periods of non-fall, near fall, and fall in the daily life of the elderly.

Perform 10 experiments in each state for a total of 200 experiments to meet the training and testing requirements of the BiLSTM model.

When constructing the model training set, this paper selects 4 males and 1 female as samples. The specific information is shown in Table 5.2.

Table 5.2 Training data set

Sample	Gender	Age	Height	Weight
Sample 1	Male	30 years old	168cm	79.6kg
Sample 2	Male	22 years old	176cm	75kg
Sample 3	Male	26 years old	171cm	67kg
Sample 4	Male	28 years old	162cm	70kg
Sample 5	Female	24 years old	168cm	55kg

Training Set of Fall Detection Model Each behavior training sequence group contains 8 pressure sensor data, 1 acceleration sensor data, 1 angular acceleration sensor data, and one status information. The remaining 15 samples were selected from 105 sensor state data to construct 5 test data sets for model testing, a total of 210 behavioral detection sequences.

The input sequence data includes 8 pressure sensor data and 1 acceleration sensor data and 1 angular acceleration sensor data, so the input node of the model can be set to 11. The output layer nodes are set to three, corresponding to the categories of the three types of human fall states. Related parameters are in Table 5.3.

Table 5.3 Related parameters

Parameter name	Parameter value
Number of input layer nodes	11
Number of output layer nodes	3
The number of layers in the hidden layer	1
Number of hidden layer nodes per layer	128
Learning rate	$1e^{-4}$
Number of instances per training	5
Forgive_bias	1

Here we use the method called random_uniform_initialize provided by TensorFlow to initialize the training parameters of the logistic regression layer, We also used the method called orthogonal_initializer to initialize the parameters of the forgetting gate, input gate, and output gate in LSTMCell。Also, set the parameter Forget_bias to 1.0 when creating a new LSTMCell. When set the parameter Forget_bias to 1.0, the LSTMCell will not pass any state, The initial value of the learning rate is set to $1e^{-4}$, and the learning rate is adjusted by using the AdaDelta method in TensorFlow. The number of hidden layer nodes is set to 128.

The quality of a fall detection algorithm can usually be judged by three indicators: Accuracy, Precision and Recall.

TP： The number of times a fall behavior is predicted as a fall behavior

FP： The number of times a non-fall behavior is predicted as a fall behavior

FN： The number of times a fall behavior is predicted to be non-falling

TN： The number of times a non-fall is predicted to be non-falling

Precision： TP/(TP+FP)

Accuracy： (TP+TN)/(TP+FN+FP+TN)

Recall： TP/(TP+FN)

Table 5.4 Test results of BiLSTM detection of fall behavior

Test set	TP	TN	FP	FN	Accuracy	Precision	Recall
Test set 1	18	9	1	1	94.73%	93.10%	94.73%
Test set 2	10	6	2	0	88.89%	83.33%	100%
Test set 3	12	7	2	0	89.47%	85.71%	100%
Test set 4	12	3	1	0	93.75%	92.30%	100%
Test set 5	14	4	1	1	90.00%	93.33%	93.33%
Total	66	29	7	3	90.47%	90.4%	95.65%

Table 5.5 Test results of Near-fall detected by BiLSTM

Test set	Total behaviour sequence	Near-fall sequence	Number of the correct Prediction	Accuracy
Test set 1	58	6	5	83.33%
Test set 2	36	4	4	100%
Test set 3	42	4	4	100%
Test set 4	32	3	3	100%
Test set 5	40	5	4	80%
Total	132	22	19	86.36%

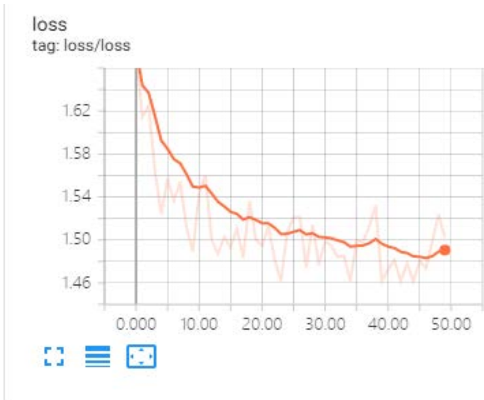

Figure 7: the loss function value of the BiLSTM

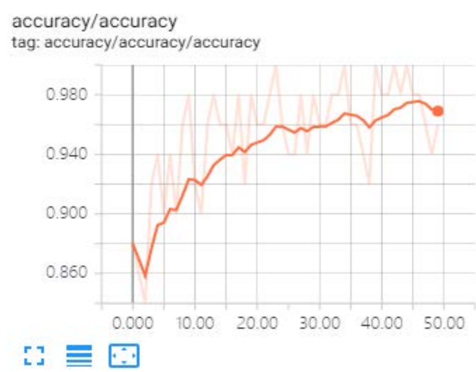

Figure8: Curve of BiLSTM classification accuracy rate

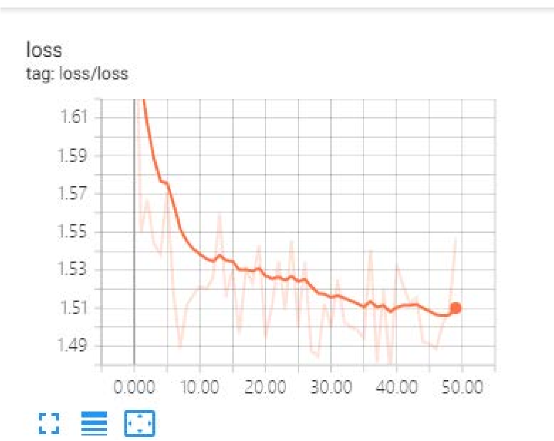

Figure 9: the loss function value of the LSTM

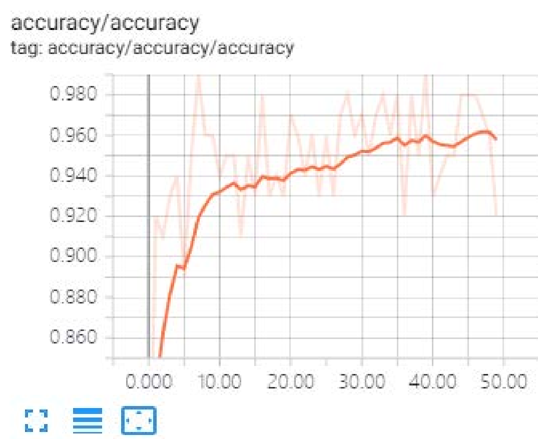

Figure 10: Curve of LSTM classification accuracy rate

Table 5.6 Compared with other fall detection algorithms

Algorithms	Accuracy	Precision	Recall
SVM	87.45%	86.9%	89.71%
LSTM	88.1%	88.92%	90.23%
BiLSTM	90.47%	90.4%	95.65%

5 Conclusion

As we can be seen from the above tables and figures, the BiLSTM has significantly improved the Accuracy, Precision, and Recall rate compared with other algorithms, indicating that the BiLSTM can be better explored and abstracted the relationship between the sensor sequence data and the state can better judge the fall behavior and more valuable near-fall behavior. With the increase of training data and enrichment and further optimization of the algorithm, the detection model can be more perfect.

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Bioremediation of Hydrocarbon Contaminated Soil: Assessment of Compost Manure and Organic Soap

[1]Akpokodje, O. I. and [2]Uguru, H.
[1]*Department of Civil Engineering Technology, Delta State Polytechnic, Ozoro, Nigeria*
[2]*Department of Agricultural and Bio-environmental Engineering Technology, Delta State Polytechnic, Ozoro, Nigeria*
erobo2011@gmail.com

ABSTRACT

This study was carried out to investigate the effect of compost manure and organic soap on hydrocarbon degradation in petroleum products contaminated soil. 10 kg of top soil collected at a depth of 0-20 cm, air dried and sieved, were poured into plastic containers. The soil samples were pounded with 1 L of spent engine oil, 1 L of kerosene, 1 L of petrol and 1 L of diesel daily for five days. The containers were placed under natural environmental conditions for three weeks to enable full acclimatization of the petroleum products with the soil. A completely randomized design comprising T1 (Polluted soil without treatment 'control'); T2 (10 kg contaminated soil + 500 g organic soap); T3 (10 kg contaminated soil + 500 g compost manure); and T4 (10 kg contaminated soil + 500 g compost manure + 500 g organic soap) was used for this study. Some physical characteristics (soil porosity and specific gravity) and Total Hydrocarbon Content (THC) of the soil samples were tested for, after the full acclimatization of the soil samples, and at the end of the 10 week experimental period, in accordance with standard methods. Results of the study showed that addition of the compost manure and organic soap to the contaminated soil samples significantly ($p \leqslant 0.05$) degraded the THC, and improved the soil physical characteristics. The result showed that the combination of compost manure and organic soap gave the best remediation result (from 957.21 mg/kg to 154.36 mg/kg), followed by organic soap (from 957.21mg/kg to 203.61 mg/kg), and then compost manure (from 957.21 mg/kg to 262.03 mg/kg). At the end of the experimental period, vegetative growth was observed in the treated soil samples; whereas, in the control soil samples vegetative growth was absent. Results obtained from this study have shown that amending petroleum products contaminated soils with compost manure and organic soap will enhance remediation of petroleum products contaminated sites.

Keywords: Petroleum products, compost manure, organic soap, THC, remediation

1 Introduction

Environmental pollution has become a problem affecting developed, developing and under-developed countries, and it is assuming a great threat to the well-being of all life forms [1]. Recently oil exploration and exploitation in Nigeria has taken a new dimension. Nigeria has the recorded largest natural gas reserve and the second largest oil reserve in Africa. Ghosh and Singh [2] reported oil exploration and exploitation, accidental and process spillage, sabotage among others, as major factors responsible for the

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environmental pollution from petroleum products. Petroleum is a complex mixture, containing significant amount of saturated alkanes, alkynes, alkenes, napthenes, highly toxic polycyclic aromatic hydrocarbons, and some heavy metals [3]. Petroleum compounds are toxic to all forms of life, and have adverse effect on the soil's physical characteristics and biochemical properties [4]. Petroleum hydrocarbon contamination has become a critical environmental issue due to its immobilization and accumulation [5-6]; and is now seriously affecting the safety of ecosystems and human health [4; 7]. Peng et al. [8] observed in their study that population of microorganisms in any soil was highly dependent on the level of petroleum hydrocarbons contaminants in the soil.

Remediation of petroleum products contaminated soils has become a great concern worldwide, due to their (petroleum products) reported adverse effects on the environment. Remediation of petroleum-contaminated soils could be achieved by either physical/mechanical (e.g excavation, burning); chemical (detergent, surfactant, degreaser), plants (phytoremediation) and biological (bioremediation) methods [4; 9]. Any remediation method adopted for the cleanup of a contaminated site depends on how suitable or efficient the method is with prospect to the prevailing site conditions. However, most of these methods have some drawbacks in completely remediating petroleum hydrocarbon contaminated soil [10]. Detailed assessment of the advantages and disadvantages of various remediation techniques are reported by United States Environmental Protection Agency [11]. The harmful effects of oil in different environments, has led to the need to develop simple adoptable remediation techniques for petroleum polluted sites using different simple and affordable methods, which may include physical, chemical and biological processes [9].

Phytoremediation is the use of plants and/or associated microorganisms to remove contain or render harmful material(s) harmless [12-13]. Phytoremediation has been shown to be effective for broad range of contaminants like petroleum products, cyanide, heavy metals, etc. Plants used for phytoremediation should be tolerant to the climatic and soil conditions of the contaminated areas [13-14]. Karenlampi et al. [15] reported four main characteristics that can make a plant suitable for the phytoremediation of contaminated soils. These factors are: the plant's ability to accumulate the extracted contaminant; the plant should be tolerant enough not only to survive in polluted soils, but to carry pollutants within their shoots; the plant should be fast growing with an amplified ability to accumulate toxins; and the plant should be easily harvestable for simple disposal [16].

Bioaugmentation is the applications of indigenous or allochthonous wide type or genetically modified microorganisms to polluted hazardous waste sites in order to accelerate the removal of undesired compounds [17-18]. Generally, bioremediation technologies can be classified as in situ or ex situ. In situ bioremediation involves treating the contaminated material at the site while ex situ involves the removal of the contaminated material to be treated elsewhere [25]. Tanee and Jude [19] reported that detergent and sawdust amendment were able to degrade the THC of petroleum contaminated soil to significant level. Some of the organic products employed are sewage sludge, cow dung, poultry waste, compost manure etc. Okolo et al. [20] observed increment in the degradation of crude oil in soil samples augmented with poultry manure; as it helps the plants to release root exudates which helped to break down the crude oil. Reference [21] suggested that the use of chicken manure to stimulate crude oil degradation in the soil could be one of the several sought-after environmentally friendly ways of combating petroleum hydrocarbon pollution in the natural ecosystem. In addition, [22] investigated the bioremediation potentials of poultry manure and cow dung on crude oil polluted soil samples. They observed that the application of poultry manure and cow dung significantly degraded the petroleum hydrocarbons in the soils. Their results further revealed that poultry manure showed superiority over cow dung in the remediation of crude oil polluted soils.

However, studies on bioremediation of petroleum products contaminated soils in Nigeria is still in the preliminary stage. Therefore, the main objective of this study was to evaluate the efficiency of organic soap formulated from oil palm bunch waste and compost manure in degrading hydrocarbons in petroleum products contaminated soil, with the ultimate goal of eliminating some toxic substances and improving the state of the soil, such as the Total Hydrocarbon Content (THC) in the soil.

2 Materials and Methods

2.1 Source of material

The spent engine oil was purchased from a mechanic workshop located at Oleh, Delta State, Nigeria; while the petrol, diesel and kerosene were obtained from a filling station located at Ozoro, Delta State, Nigeria.

2.2 Soil sample collection and contamination

Top soil (0 – 20 cm) depth was collected from the irrigation station of Delta State Polytechnic, Ozoro, Nigeria. The collected soil sample was air dried in the laboratory at ambient temperature, and later sieved with a 2 mm stainless steel sieve to remove all stones and other debris. The soil samples were contaminated in accordance with standard methods as stated by [13]. 10 kg of the soil was weighed into each plastic containers perforated at the bottom and artificially polluted with 1 L of spent engine oil, 1 L of kerosene, 1 L of petrol and 1 L of diesel daily for five days. The set up was allowed to stand for three weeks for full acclimatization of the petroleum products with the soil under natural environmental conditions in an open space.

2.3 Organic soap preparation

Palm fruit bunch waste was collected from the palm oil mill of Delta State Polytechnic, Ozoro, Nigeria. The waste was sundried and burnt into ashes. After that, the ashes were dissolved in distill water to obtain a heterogeneous solution. The solution was filtered with whatman No1 filter paper, and the filtrate obtained evaporated to dryness. Crystals recovered from the dried solution was used to prepare the organic soap according to standard method.

2.4 Composting of the compost manure

Wood sawdust was obtained from timber sawmill located at Ozoro, Delta state, Nigeria, while the poultry droppings and cattle dungs were obtained from the animal farm situated at Delta State Polytechnic, Ozoro. The three constituents (saw dust, poultry waste and cattle dung) were composed using a mixing ratio of 10%:45%:45% (volume to volume), and composed using the passively aerated static pile method for a period of three months.

2.5 Remediation set up

The concentration levels (amounts) of compost manure and organic soap used as amendment in the remediation are presented in Table 1.

Table 1: Experimental set up

Treatment	Concentration
T1	10 kg contaminated soil (Control)
T2	10 kg contaminated soil + 500 g compost manure
T3	10 kg contaminated soil + 500 g organic soap
T4	10 kg contaminated soil + 500 g compost manure + 500 g organic soap

The remediation set up was laid out in a completely randomized design (CRD) with three replicates.

In the compost manure treatment, the compost manure and the soil sample were thoroughly mixed to obtain a homogeneity mixture. While in the organic soap treatment, the organic soap was divided into two equal parts. One part was thoroughly mixed with the soil sample to obtain a homogeneity mixture; while the other part was dissolved in one litre of distil water to form a homogeneity mixture, before it was poured gently into plastic container containing the soil sample. All the plastic containers (control and treated) were placed in an open space, under atmospheric conductions (rainfall, sunlight, relative humidity, temperature, dew, etc.) for an experimental period of ten weeks. At the end of the ten weeks, another round of physiochemical and THC tests were carried out on the soil samples.

2.6 Determination of the Total Hydrocarbon content

The Soxhlet Extraction Method [23] was used for the determination of Total Hydrocarbon Content (THC) of the soil samples.

2.7 Soil physical characteristics analysis

The following physical characteristics analysis (porosity and specific gravity) were carried out on the contaminated (after full acclimatization period), and the remediated soil samples. The soil porosity and specific gravity were determined by using standard methods [24].

2.8 Statistical evaluation

Data obtained from this study was analyzed using Analysis of variance (ANOVA) according to SPSS data analysis package (2018 version). The mean separation of parameters investigated was done by using Duncan's Multiple Range tests at 95% confidence level.

3 Results and Discussion

3.1 Physicochemical analyses of the compost manure and organic soap

The physicochemical properties of the compost manure and organic soap used for the bioremediation experiment are presented in Table 2.

Table 2: Physicochemical Properties of compost manure and organic soap used for bioremediation

Parameter	Compost manure	Organic soap
pH	8.3	9.1
Total nitrogen (mg/kg)	9.23	5.61
Phosphorus (mg/kg)	427.91	3220.56
Potassium (mg/kg)	1687.58	4951.44
Moisture (%)	13.09	21.56

The analysis of variance (ANOVA) results presented in Table 3 showed that the various treatment methods had significant effect on all the parameters investigated in this study. The results showed that Treatment 4 (contaminated soil + compost manure + organic soap) had the highest remediation impact on the contaminated soil, followed by Treatment 3 (contaminated soil + organic soap), and then Treatment 2 (contaminated soil + compost manure) while Treatment 1 (contaminated soil 'control') had the least remediation effect.

Table 3: Analysis of variance of treatment methods on the THC, porosity and specific gravity of contaminated soil

Source of vibration	df	Sig
THC	4	5.64E-13
Specific gravity	4	2.65E-08
Porosity	4	2.63E-07

3.2 Bioremediation of the THC

The result of biodegradation of THC in the petroleum products contaminated soils at the end of the experimental period is shown in Figure 1. At the end of the 10 week period, the contaminated soil samples treated with the combination of 500 g compost manure and 500 g organic soap (T4) gave the best result with 83% biodegradation, followed by the soil samples treated with organic soap (T3) with 79% biodegradation, and then the soil treated with compost manure (T2) with 72% biodegradation, when compared to the un-treated 'control' soil that showed 29% biodegradation of the THC. The differences in the results obtained might be due to different nutrient concentrations of the treatment materials used. The biodegradation potentials of the treatment materials (compost manure and organic soap) can also be attributed to the high absorbent material present (from the sawdust) in the compost manure; and the demulsification effect of the organic soap.

During the bioremediation process, the compost manure provides nutrients that will energize the hydrocarbons degrading microorganisms. Organic nutrients stimulate degradation capabilities of the indigenous microorganisms thus allowing the microorganisms to break down the organic pollutants at a faster rate [26]. Apart from the demulsification of petroleum products by the organic soap during the bioremediation process, the organic soap provides suitable environment for the soil microorganisms, by supplying them some essential nutrients (Nitrogen, potassium and phosphorus). Potassium, phosphorus and nitrogen are some of the chief constituents of the organic soap (Table 2). Nitrogen and phosphorus compounds help to remediate oil polluted soil, as they accelerate the biodegradation of the petroleum hydrocarbon in the soil [27]. Similar results were observed in hydrocarbon contaminated soils amended with poultry and pig manure compost [28-29]. Ogboghodo et al. [21] observed that chicken manure was able to degrade hydrocarbons in crude oil contaminated soil by 75% within two weeks, due to their high nitrogen content.

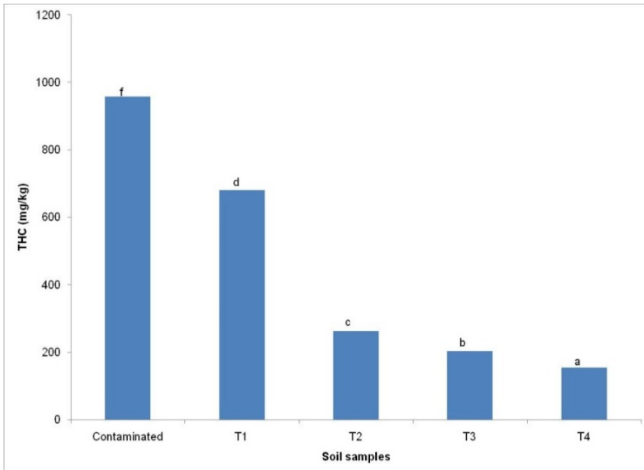

Figure 1: Biodegradation of THC in a contaminated soil using compost manure and organic soap.

Columns with the same common latter are not significantly different ($p \leqslant 0.05$) according to Duncan's multiple ranges test

3.3 Soil physical characteristics

Porosity

Apart from the degradation of the THC in the soil samples at the end of the experimental period, the results presented in Figures 2 and 3 showed that the treatments significantly ($p \leqslant 0.05$) influenced the physical characteristics of the contaminated soil samples. The results (Figure 2) showed that the combination of the organic soap and compost manure had the greatest bioremediation effect on the soil porosity. Combination of the organic soap and compost manure treatment improved the soil porosity from 15.33% to 32.40%; the organic soap improved the porosity from 15.33% to 29.01 %; while and the compost mature improved the soil porosity from 15.33% to 26%, within the 10 week experimental period. There was no significant ($p \leqslant 0.05$) difference between the porosity of the soil sample treated with organic soap, when compared with the soil sample treated with compost manure (Figure 2). As seen in Figure 2, the porosity of the control soil increased significantly ($p \leqslant 0.05$), when compared to the initial contaminated soil samples. The significant improvement in the control soil samples porosity can be attributed to the leaching of the hydrocarbons during downpour, and evaporation of some of the volatile hydrocarbons, since the experimental set up were kept in the open space, exposed to environmental conditions. Petroleum products blocked soil air pores (reduced the porosity), thereby lowering the water holding capacity and aeration in the soil [30]. This deprived the soil its oxygen and water holding abilities, which are necessary for plant and microbial growth.

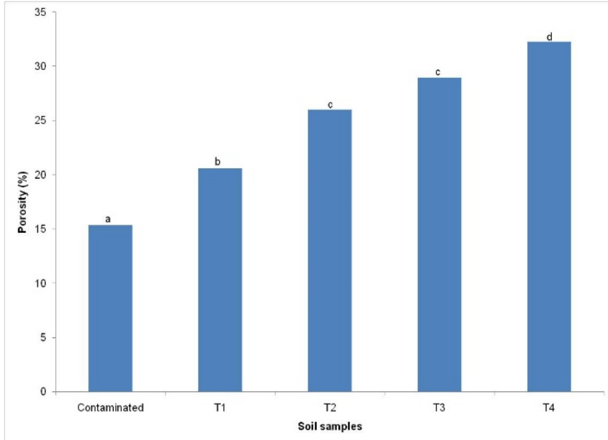

Figure 2: Effect of compost manure and organic soap on the porosity of the contaminated soil samples

Columns with the same common latter are not significantly different ($p \leqslant 0.05$) according to Duncan's multiple ranges test

Specific gravity

The results presented in Figure 3 showed that the treatment combination of organic soap and compost manure had the statistical highest remediation effect on the soil specific gravity. The mean specific gravity of the soil samples increased from 1.59 to 2.18, after treatment with the combination of organic soap and compost manure, within the 10 week experimental period. Organic soap was able to increase the specific gravity of the soil from 1.59 to 2.04; while and the compost manure increased the soil specific gravity from 1.59 to 1.90 within the 10 week experimental period (Figure 3). As shown in the chart presented in Figure 3, there was no significant ($p \leqslant 0.05$) difference between the specific gravity of the contaminated soil and the control soil samples at the end of the experimental period. Similar results were reported by [31-32]. Amadi et al. [32] stated that high hydrocarbon content of soils may affect the physicochemical properties of the soil which may in turn affect the agricultural potentials and productivities of such soils.

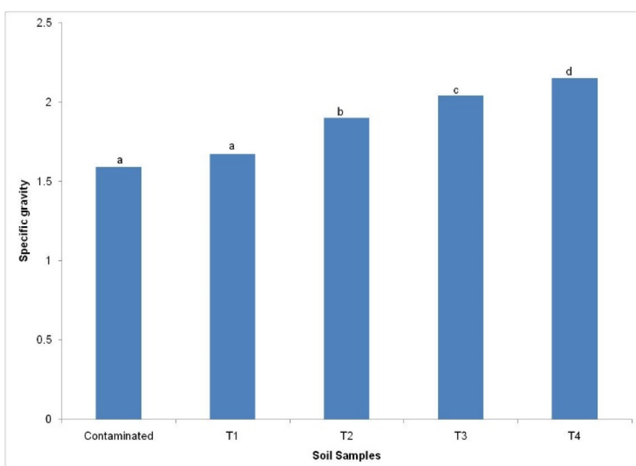

Figure 3: Effect of compost manure and organic soap on the specific gravity of the contaminated soil samples

Columns with the same common latter are not significantly different (p ≤0.05) according to Duncan's multiple ranges test

3.4 Vegetative growth

As shown in Figure 4, vegetative growth was observed in the treated soil samples, when compared to the untreated soil sample which showed no form of plant life. Plants growing on the treated soil samples will further aid the degradation of the THC in the soil and improve the soil's physical characteristics, as they have the ability to degrade petroleum products in the soil and in water bodies. Plants root exudates help to degrade toxic organic chemicals and act as substrates for bacteria in the soil, which improves the plants phytoremediation potential [4; 33]. Absence of vegetative growth in the control soil sample confirms the toxicity of petroleum products to soil microbial activity required for effective degradation [34]. Vegetative growth found in the treated soil was stimulated by the compost manure used as the treatment materials. Merkl et al. [35] reported higher degradation of petroleum hydrocarbon in vegetated soils compared to non-vegetated soil. These results are similar to results from previous researchers. Okolo et al. [20] observed degradation of crude oil in soil amended with poultry manure; [36] reported that organic manures have the potential of degrading hydrocarbon in contaminated soils by increasing the total heterotrophic microbial growth and activity. The extent poultry manure degrades crude oil in contaminated soil depends on the presence of other soil amendments [20]. Addition of compost manure helps to improve the physicochemical properties of petroleum products contaminated soils; hence, enhancing the remediation of these contaminants and improving oil biodegradation rates.

Figure 4: Effect of compost manure and organic soap on the vegetative growth of the contaminated soil samples

4 Conclusion

This study was carried to evaluate the bioremediation potentials of compost manure and organic soap. Top soil samples were contaminated mixture of petroleum products, and remediated for 10 weeks. The results of the study showed that the contaminated soil treated with combination of compost manure and organic soap recorded the highest hydrocarbon biodegradation of 83%, when compared to the single treatment of compost manure (72%) or organic soap (79%). The different results obtained were due to different nutrients concentration of the treatment materials. In terms of the soil physical characteristics, results obtained from the study, that both treatment materials significantly improved the soil porosity and specific gravity. The combination of the organic soap and compost manure had the greatest bioremediation effect on the soil porosity and specific gravity. At the end of the experimental period, vegetative growth was found on the treated soil samples; whereas, vegetative growth was absent in the control soil samples. Results obtained from this study further showed that utilization of organic waste materials in the bioremediation of contaminated soils. However, more researches involving other organic waste materials are crucial in order to identify suitable organic waste materials to be used in bioremediation of hydrocarbon compounds.

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A Survey of Emerging Techniques in Detecting SMS Spam

[1]Sahar Saad Alqahtani, [2]Daniyal Alghazzawi
[1,2] *Department of Information Systems, Faculty of Computing and Information Technology at King Abdulaziz University, Jeddah, Saudi Arabia;*
sqahtanie@kku.edu.sa; dghazzawi@kau.edu.sa

ABSTRACT

This In the past years, spammers have focused their attention on sending spam through short messages services (SMS) to mobile users. They have had some success because of the lack of appropriate tools to deal with this issue. This paper is dedicated to review and study the relative strengths of various emerging technologies to detect spam messages sent to mobile devices. Machine Learning methods and topic modelling techniques have been remarkably effective in classifying spam SMS. Detecting SMS spam suffers from a lack of the availability of SMS dataset and a few numbers of features in SMS. Various features extracted and dataset used by the researchers with some related issues also discussed. The most important measurements used by the researchers to evaluate the performance of these techniques were based on their recall, precision, accuracies and CAP Curve. In this review, the performance achieved by machine learning algorithms was compared, and we found that Naive Bayes and SVM produce effective performance.

Keywords: SMS spam detection, Text classification, SMS spam filtering, SMS spam dataset, Text features extraction.

1 Introduction

By the advancement in technology of mobile communications and mobile phones expansion, Short Message Service (SMS) has turned out to be a popular mode of communication due to its ease of operation and less cost. SMS technique is used to send a text message from one mobile device to another. Some of these messages that reach the user's device are unwanted and annoying which called spam. In the smartphones age, user has confidential and personal information such as passwords, images, numbers of credit card, contact lists that stored on these phones, making those users more vulnerable to cyber-attacks by spam SMS. Spam may leak sensitive information, privacy invasion, or access unauthorized information. Spammer are people with unethical activities can access data in smartphone without the end-user knowledge, exposing the privacy of the user to the path that results in financial or functional loss. Nowadays, Spam messages appear to be increasing where it is annoying users and also dramatically lose their data. This kind of problems has inspired many researchers to develop collections of techniques to assist effectively in detect and prevent spam SMS. The availability of SMS datasets to be applied in train and test techniques in order to detect spam in SMS are small sized and still limited. Moreover, the availability of features number needed to detect spam messages in text are less, this is due to the text messages length is short.

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The objective of this paper is to review the emerging technologies used in detect SMS spam. Our survey includes various datasets of SMS spam used by researchers. This work also provides comparison and analysis of the different techniques on different datasets and their performance according to their accuracies, precision and recall.

The structure of our paper is as follows: Section 2 presents overview of detecting SMS spam. In section 3, we review applications of researchers in detecting SMS spam. The techniques used in the process of filtering SMS spam were investigated and displayed in section 4. The feature extraction process is discussed in section 5 while section 6 presents the available and used dataset of SMS. The measurements used by researchers to evaluate the performance of the techniques used were discussed in section 7. Finally, the paper concludes in last section.

2 Overview of Detecting SMS Spam

Over the past decade, spam SMS number causing issues to users through advertisement has been increased dramatically. consequently, researchers have produced different techniques of spam detection over last years to achieve the results accuracy. Recently, there are many published papers by researchers whose working in this field. In the context, spam messages are very similar to spams in email that usually have several business interests. Spam messages in SMS is typically utilized for spreading phishing links and commercial advertising. Spammers in commercial advertising use malware for sending SMS spam as it is illegitimate in many countries [1]. The service of SMS has restricted number of characters, that involve a few symbols, numbers and alphabets. Usually the pattern of SMS spam seems is asking the users to visit some URL, reply by SMS or call a number. In general, spams in SMS can be detected by reviewing and examining contents of message that means features of content. The pattern can be observed from the output of simple queries on the spam dataset. Spammers are usually utilizing minimal volumes and advanced methods in order to avert detection that seems a worrying dynamic. They transmit tiny amounts of SMS spam to observe how the infrastructure of operator in SMS reacts and then identify the policies of volume limits [2]. Based on that, content-based filtering technology is very important to counteract the rising threat in spam messages. There is a continual discussion on SMS spam filtering where the researchers have come up with technical measures that concrete for tackling this issue. The majority of discovered practices and measures can be utilized for dealing with SMS spam. From the literature, the most widely accepted technique and the prominent ones is Bayesian filters. In the following sections we will review all the researchers' applications to detect SMS spam, what techniques have been used, which data set has been applied, and what their method is to extract features from messages.

3 Application of Detecting Spam In SMS

Recently, the research on detecting the SMS spam messages was the focus of attention of researchers worldwide. In this section, we attempt to present all the previous studies conducted to detect SMS spam messages sent to mobiles' users. The application of filtering spam in short messages differed, according to these studies as we shall see in this section. Whereas Support Vector Machine (SVM), Convolutional Neural Network (CNN), Latent Dirichlet Allocation (LDA), Logistic Regression (LR), Random Forest (RF), AdaBoost, Artificial Neural Network (ANN), k-Nearest Neighbor (k-NN), Decision Tree (DT), Optimum-Path Forest (OPF), Fisher's linear discriminate analysis (FDA), Non-negative Matrix Factorization (NMF) and Naive Bayes (NB) were the approaches used in these studies. The description of these technologies in details is presented in section 4.

In 2018, Mehul et al. used different eight machine learning algorithms i.e. SVM, NB, DT, LR, RF, AdaBoost, ANN and CNN. They analyzed and compared the detection capability of these classifiers on two various datasets i.e. 'SMS Spam Collection V.1' and 'Spam SMS Dataset 2011-12'. All of these classifiers have been evaluated based on their accuracies, precision, recall and CAP Curve values. They approved that CNN classifier achieved the highest accuracy of 99.19% and 98.25% on the two used datasets. Among the remaining used algorithms, NB and SVM showed good outcomes, very close to convolutional neural network on both the data sets [3].

In this context, Neelam and Ankit in [4] used four algorithms from machine learning field which are NB, LR, DT, and RF on 'SMS Spam Corpus v.0.1' in addition to 200 messages collected manually. They also studied SMS spam characteristics deeply and then prouduce ten features that are presence of mathematical symbol, URLs, dots, special symbols, emotions, lowercased words, uppercased words, mobile number, keyword specific for spam and not spam, message length. They evaluated these classifiers based on the following criterias, that will be discussed in section 6, f1 score, true negative (TN), true positive (TP), false negative (FN), false positive (FP) accuracy, recall and precision. The best algorithms of their proposed approaches in the process of detecting SMS spam was Random Forest that accomplished 1.02% false positive rate and 96.5% true positive rate.

On other hand, researchers in [5] planned to feed the classification algorithms essentially with two features: the matrix of count vectorizer and the message length on one dataset i.e. 'SMS Spam Collection V.1' by using Logistic Regression, Random Forest and Naïve Bayes classifiers. Their priorities in ranking the used classifier based on accuracy of algorithm in detecting spam messages. They found that NB outperforms RF and LR algorithms in classifying SMS spam where it achieved a high accuracy (98.445).

Authors in 2016 [6] perform many modifications in Support Vector Machine (VSM) method in order to address the difficulties in filtering issue of spam SMS. The dataset they are working on has been collected from 'Dahan Tricom database'. The result of their technology has been evaluated by precise, recall and F1 score that deployed in Dahan Tricom Corporation and this technology will be applicable in SMS commercial companies.

Traditionally, convolutional neural network has been utilized for problems related to classifying image. The paper by Milivoje et al. [7] in 2018 ran counter to this idea by using CNN for classifying SMS spam messages. Crucial step in their work was preprocessing the data by removing stop words, tokenization, reducing text to lower case where they are working on 'SMS Spam Collection V.1' dataset. They prove that their proposed CNN for spam classification can produce the best compared to several other machine learning techniques where it achieved accuracy of 98.4% and AUC score of 0.955.

British English SMS Corpora (BEC), UCI Machine Learning (UCI) and Dublin Institute of Technology (DIT) are three dataset that used by Nurul and Mohd [8]. They consider that numbers and symbols in dataset should not be cleaned because it may help in the detection process beside the SMS length and keywords. They train and test these datasets on four classifiers i.e. Decision Tree (DT), Support vector machine (SVM), k-Nearest Neighbor (k-NN), Naïve Bayes (NB). They found that all of these algorithms correctly classified the SMS spam in the three used datasets.

Research's Naresh aims to determine and category spam SMS from 'SMS Spam Collection V.1' dataset and also to identify the priority SMS messages. He used Non-negative Matrix Factorization (NMF) and Latent

Dirichlet Allocation (LDA) in combinations with Support Vector Machine (SVM) and Naïve Bayes (NB). The performance of these classifiers measured by accuracy and f score that showed that SVM classifier produces the best in filter SMS spam and classifying the priority SMS [9].

Some researchers focus on suggesting methods to extract features from messages. Such as Noura et al. [10] that used topic modelling technique such as latent Dirichlet allocation to extract the features from 'SMS Spam Collection V.1' dataset. They tried many algorithms with these features and their result are compared against other spam detection algorithms. They reported that their suggested method accomplishing over 97% accuracy comparing favorably to better reported classifiers displayed in the literature. In this context, Jialin et al. in 2016 [11] suggest a method for filtering SMS spam called a Message Topic Model (MTM) that work on two different datasets: 'DIT SMS Spam Dataset' and 'SMS Spam Collection v.1'. The proposed method compared with Support Vector Machine and the standard Latent Dirichlet Allocation on the same dataset and they found that Message Topic Model is more efficient for filtering spam in SMS spam.

In 2015, the paper of Dheny et al. [12] used OPTIMUM-PATH FOREST on 'SMS Spam Collection V.1' dataset with preparing a dictionary of 12,622 words as features that help algorithm to perform the classification task without any other preprocessing technique on the data. They validated their approaches against with k-NN, Artificial Neural Networks classifier and Support Vector Machine. They have shown promising results for their used classifier as there is no need for a high computational load compared with SVM classifier and it correctly classified all ham messages.

4 Techniques Used for Detecting SMS Spam

In the literature, various preprocessing techniques have been implemented on various SMS spam datasets to detect spam in short text messages. A brief description of these techniques is presented as follow:

4.1 Naive Bayes (NB) [13]:

It is a classification technique based on theorem of 'Bayes' that assume independence among predictors. This classifier of Bayesian supposes that there is no relationship between presence of a specific feature in one class and the existence of any other features. Even if there are dependencies between the existence of the feature with each other, this classifier will treat all desired properties as independent that contribute in the probability score. The Naive Bayes classifier is still simple and sturdy in the case of the dimensionality of desired input is high. Multinomial Naive Bayes (MNB) is a new advanced version of Naive Bayes classifier. The basic advancement is the presence of independency among document class and length. this classifier includes multinomial distribution that works well for data type that is countable like the words inside a text or document. So, with classifier of NB is a conditional independency between each the feature in the model, while classifier of MNB is a particular case of a Naive Bayes algorithm that utilize a multinomial distribution for each feature. In our reviewing process, we found that using Naive Bayes algorithm in SMS spam filtering the first most prominent technique used by researchers as its applied by [3][4][5][8][9].

4.2 Support Vector Machine (SVM) [14]:

It is a characteristic classifier that is vastly utilized for the task of classification. The algorithm of SVM plots all item in n-dimensional space as a point supposing each feature value as a specific coordinate value. Then it constitutes a line which divides the full data into two variously data groups. The adjacent points in these groups will be the furthest from the dividing line. In our reviewing process, we found that using support vector machine algorithm in SMS spam filtering the second most prominent technique used by researchers as its applied by [3][7][8][9].

4.3 Decision Tree (DT) [15]:

DT is an algorithm based on supervised learning that is usually used for tasks related to classification. This algorithm works with both continuous and categorical variables. Initially, the algorithm will split the population for many homogeneous groups that is done according to the basis of independent variables or significant attributes. As decision tree is non-parametric, the requirement for examining existence of outlier or separation data linearity is not needed.

4.4 Random Forest (RF) [16]:

It refers for a crew of Decision Trees. Meaning that, the RF classifier is a crew learning mode involving set of decision trees. This classifier works as vote for a specific class by each tree to classify a new object. The class that have the greatest votes number will deciding the label for classification.

4.5 Logistic Regression (LR) [17]:

It is binary classification techniques that is utilized in estimate the discrete values based on group of independent variables. In most comparative terms, logistic regressions produce the event probability through fitting them into logistic functions that assists in the prediction process. These functions are mostly utilized as sigmoid.

4.6 AdaBoost [18]:

AdaBoost is an algorithm of metamachine learning that is refers as Adaptive Boosting. Its utilized to arise the classifier performance by using weakly classifiers in order to merge them into a strong classifier. The boosted classifier output relies on the weighted total of all weakly classifiers output. Although this technique is performing more accurate prediction, it occupies more time to build the adaptive boosting model.

4.7 Artificial Neural Network (ANN) [19]:

They are techniques for statistical model of nonlinear data with a complex relation among outputs and inputs. They learn from observing datasets that will work on. they are seeming as tool for approximate the random functions that assist in estimate the efficient method in achieving solution. One such network is convolutional neural network (CNN) that will be described in the next section.

4.8 k-Nearest Neighbor (k-NN) [20]:

It is one of the simplest machine learning algorithms. The KNN algorithm used for predictive problems in both regression and classification task. It is characterized by easy of interpretation with low calculation time. Even with this simplicity, it gives extremely competitive outcomes. This algorithm supposes that similar things similar things are near to each other where similarity, sometimes called closeness, proximity, or distance, are considered through calculate the distance among datapoints on a graph.

4.9 Convolutional Neural Network (CNN) [21]:

This network is also known as a ConvNet, it's a specific type of artificial neural network that utilizes supervised learning perceptron. This type of learning is utilized to data analysis. There are a broad range of implementation including convolutional neural network such as image processing (traditionally) and natural language processing (nowadays).

4.10 Optimum-Path Forest (OPF) [12]:

Optimum-Path Forest is a classifier algorithm that model the pattern recognition as the problem of graph partition where samples are considered as nodes in graph that connected according to the adjacency relations of them. The segmentation of graph is ruled by the process of competition between several prototypes (key nodes) aiming at grab the surviving samples that leads to cost in optimum path.

4.11 Fisher's linear discriminate analysis (FDA) [7][11]:

Linear discriminate analysis is a classification technique that develop by Fisher. It can classify the multi-dimensional data in multiple classes according to the separating line between the components. It is statistical method used to model the predictors distribution separately in every response class. After that, Bayes' theorem will be used for estimating the probability. This method can be used in statistics, machine learning and pattern recognition for finding a linear features combination that separates two or more classes of events.

4.12 Latent Dirichlet Allocation (LDA) [7] [9] [11]:

It is topic modeling technique used for discovering the topics in the collections of data that have certain probabilities. Set of similar topics constitute mixture in the space where the topic is a set of words. In the literature, some of researchers use LDA to extract the feature form data to be ready to apply by any machine learning algorithms.

4.13 Non-negative Matrix Factorization (NMF) [9]:

It is a text mining technique where their algorithm has been employed in the process of features extraction. It has a predictive power that make it useful when there are many ambiguous attributes with e weak predictability. This algorithm can introduce significative patterns, themes or topics.

5 Features Extraction Process

Successful methods of machine learning rely primarily on selecting the convenient set of features for the issue involved. The feature selection must be heavily related to type of message to arise the spam detection accuracy [10]. It is also necessary to delete the noisy features and choose the best messages features to classify them. Moreover, selecting features carefully also facilitates calculation, avoiding over-fitting and increasing accuracy [11]. Some of researchers focused on engineering feature to produce the best messages features which would be assisted in message representation and classification. They used specific methods from text mining field such as Non-negative Matrix Factorization and Latent Dirichlet Allocation (LDA) that are described in the previous section. In this section, we display the different messages features suggested in various reviewed papers. Part of these features may also perform as rules of classification and qualified by users that leads to personalization in filtering process. From the literature, we can summarize the proposed features set that have been utilized for filtering spam in SMS and improved the classification algorithms performance on SMS spam data. In Table 1, we introduce these feature sets.

Table 1. Most Popular Features Extracted in The Reviewed Papers.

Feature name	description
Spam Keywords	Generally, spammers attract users by using some suspicious keywords in spam messages like delivery, Prize, claim, Please, Congrats, cash, visit, video, mins, service, awards, accident, free, send, etc.
Special symbols	Spammers tend to utilize special symbols. Like • "$" is utilized to refers 'money', 'dollar' in spam SMS. • "!" is utilized to attract the user attention. like CONGRATULATIONS! WINNER! • Emotion and dots usually used by people in chatting and refers for legitimate messages. Such as (: , :(etc. • Mathematical symbol like + utilized as free services messages.
URLs	Spammer tend to ask users to visit some URLs in order to steal their private information.
lowercased and uppercased words	Lowercased and uppercased words in messages that utilized to seek attention of user. Like: FREE, PRIZE, ATTENTION, RINGTONE, WON, etc.
Mobile Number	Spam messages are usually containing mobile number.
Message Length	Spam messages tend to be longer in size than the legitimate messages.

6 SMS Spam Dataset

Accessibility to the required data set is one of the challenges researchers often face in conducting a successful search for filtering or classifying SMS messages. Unlike spam in email that has a huge diversity of datasets, filtering of mobile spam has very few datasets. Lacking in the presence of public, available, real databases leads to compromises in developing various methods. Choosing a SMS spam dataset is a critical stage in measuring the performance of SMS filtering techniques methods as it is will work on it. Different repositories have been utilized by researchers for constructing a comprehensive dataset. Most researchers tend to use two or more sets of data in order to analyze the proposed methods. In this review, we have introduced the credible research datasets utilized by authors to experiment the algorithms. These SMS spam datasets are: SMS Spam Collection V.1, Spam SMS Dataset 2011-12, UCI SMS Spam Dataset, British English SMS Corpora (BEC), Dublin Institute of Technology (DIT), Dahan Tricom SMS corpus. In details, the description of these datasets is presented in Table 2. SMS Spam Collection V.1 developed by Tiago is the most widely used by researchers. It is consisting of four different datasets as follow:

- National University of Singapore (NUS): It is a set of 3375 non spam SMS messages
- Grumbletext: It includes 425 spam SMS.
- Caroline Tag's PhD: It is a collection of 450 SMS ham messages

- SMS Spam Corpus v.0.1 Big: It includes of 1,002 ham and 322 spam messages.

Table 1. Most Popular SMS Dataset.

Datasets	Total no. of SMS	Ham Messages	Spam Messages	Used references
SMS Spam Collection V.1	5574	4827	747	[3][12][10][11][9][5][7]
Spam SMS Dataset 2011-12	2000	1000	1000	[3]
UCI SMS Spam Dataset	5572	4825	747	[8]
British English SMS Corpora (BEC)	875	450	425	[8]
Dublin Institute of Technology (DIT)	1353	-	1353	[8][11]
Dahan Tricom SMS corpus	20000	8000	12000	[3]
SMS Spam Corpus v.0.1 Big	1324	1002	322	[3][7][5][12][10][4][9][11]
SMS Spam Corpus v.0.1 Small	1084	1002	82	[4]

7 Performance Evaluation

In this section, the most significant performance indicators that evaluate the algorithms' strength in filtering spam were reviewed. There are different criterions of performance measurement such as Accuracy, F1 score, Recall, Precision, Cumulative Accuracy Profile (CAP) Curve and Receiver Operating Characteristics (ROC) Curve used by authors in reviewed researches. These are the standard metrics to evaluate the effectiveness of any spam detection techniques. It is essential to select the right metrics of performance to gain the required information for systems validation or comparison. Most of researchers compare and analyze the spam filtering ability in the different algorithms according to their result of performance metrics. The terminologies of these performance metrics are explained in Table 3. To understand these metrics, we should define four related terms as follow:

- True positive (TP): The spam messages rate that were accurately categorized as spam messages by the used classifier
- False positive (FP): The ham messages rate that were incorrectly classified by the used classifier as spam messages
- True negative (TN): The ham messages rate that were accurately classified by the used classifier as ham messages.
- False negative (FN): The spam messages rate that were wrongly categorized by the used classifier as ham messages.

Table 3. Units for Magnetic Properties.

Evaluation metrics	Mathematical equation	definition
Accuracy	$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$	It identifies the all messages proportion that have been classified correctly.
Recall	$Recal = \frac{TP}{TP + FN}$	It identifies the legitimate messages proportion that have been correctly classified,
Precision	$Precision = \frac{TP}{TP + FP}$	It identifies the all correctly classified messages proportion that are actually legitimate.
F1 score	$F1\ score = \frac{2 * precision * Recall}{precision + Recall}$	It is referring to the harmonic mean of Recall and Precision
AUC-CAP	$Accuracy\ ratio\ by\ CAP\ curve = (area\ under\ model's\ CAP\ curve) / (area\ under\ model\text{^}'\ sCAP\ curve)$	It is utilized to assist and compare machine learning algorithms that shows the positive outcomes cumulative number on the y-axis and the corresponding classifying parameters cumulative number on the x-axis [8].
AUC-ROC	$Accuracy\ ratio\ by\ ROC\ curve = 2 *\ area\ under\ ROC\ curve - 0.5$	It is used to explore the tradeoffs between various classifiers on a costs range. the large area under the curve represent the best performance [8].

8 Discussion

Nowadays, automating the process of detecting spam in SMS is still a challenge task. There are three basic issues hindering the algorithms advancement in this research domain: the lack of real and public datasets, the text is full of abbreviations and idioms, decrease the number of features extracted from the message. To fill some of these gaps, we presented the commonly used data sets and some of the practical and effective methods used by the researchers. We found that 'SMS Spam Collection V.1' are the most commonly dataset used among researches as it is used by [1][6][7][10][9][5][4] in their work followed by Dublin Institute of Technology (DIT) SMS dataset that used by [2][10]. From the survey presented, we observe that most of researchers filtering spam in short text messages by using techniques from two major fields: machine learning and topic modelling. Topic modelling usually used to enhance the process of feature extraction of dataset that assist in increasing the performance of used algorithm. The most algorithms used in the reviewed research: Decision Tree (DT), Support Vector Machine (SVM), Logistic Regression (LR), Naive Bayes (NB), Random Forest (RF), AdaBoost, Artificial Neural Network (ANN), k-Nearest Neighbor (k-NN), Optimum-Path Forest (OPF), Fisher's linear discriminate analysis (FDA), Latent

Dirichlet Allocation (LDA), Convolutional Neural Network (CNN) and Non-negative Matrix Factorization (NMF). From the literature, the most widely accepted technique and the prominent ones is Bayesian filters that applied by [3][4][5][8][9]. However, the second most prominent technique used by researchers was Support Vector Machine as its applied by [3][7][8][9]. In this context, convolutional neural network showed great achievement in detecting spam in SMS compared by the traditional algorithms. As well, it also attains in textual data the highest accuracy. CNN's accomplishments have opened up the broad research aspect of its implementation in classifying the texts. On another hand, artificial neural networks, AdaBoost and Optimum-Path Forest have not been broadly utilized for SMS classification. In this review, the performance achieved by machine learning algorithms was compared, and we found that Naive Bayes and SVM produce effective performance. In most of researches, the measurements of algorithms performance are done by calculating the Accuracy, F1 score, Recall and Precision. Accuracy is the famous standard in evaluating the performance of the classifier algorithms. There is one research that add Cumulative Accuracy Profile (CAP) Curve and Receiver Operating Characteristics (ROC) Curve in measuring the classifier performance. In summary, there is a continual discussion on SMS spam filtering where the researchers have come up with technical measures that concrete for tackling this issue. The majority of discovered practices and measures can be utilized for dealing with SMS spam.

9 Conclusion

Short Message Service (SMS) is the most common and cheapest way of communication for mobile's users. Some company or Spammer used this service for marketing that caused in sending unwanted spam message that disturb mobile's users. To avoid this problem, researchers have proposed techniques for filtering spam SMS. In this paper, we have reviewed the emerging technologies used by researchers in detect SMS spam. Machine learning and topic modelling were the most widely techniques used by researchers. Topic modelling usually used to enhance the process of feature extraction of dataset that assist in increasing the performance of used machine learning algorithm. The success of machine learning techniques in filtering SMS spam depends primarily on selecting a suitable SMS dataset and also extracting a set of features for the problem involved. In this work, we present various SMS datasets and different features of SMS spam messages that have proposed in various reviewed papers. The availability of SMS datasets to be applied in train and test techniques in order to detect SMS spam are small sized and still limited. The most commonly dataset used among researches was 'SMS Spam Collection V.1'. Moreover, the availability of features number needed to detect spam messages in text are less, this is due to the text messages length is short. Also, our survey provides comparison and analysis of the different techniques on different datasets and their performance according to their accuracies, precision and recall. This review discover that the majority of papers are based on the Bayesian network and support vector machine to construct SMS spam classifiers and they also achieved the highest accuracy.

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Artificial Soul Optimization - An Invention

[1]Satish Gajawada, [2]Hassan M.H. Mustafa
[1]Independent Inventor and Scientist
Founder and Father of Artificial Human Optimization Field
Alumnus, Indian Institute of Technology Roorkee
[2]Faculty of Specified Education, Dept. of Educational Technology,
Banha University, Egypt
Grand Father of Artificial Human Optimization Field
satish.gajawada.iit@gmail.com, prof.dr.hassanmoustafa@gmail.com

ABSTRACT

The Soul is eternal and exists even after death of a person or animal. The main idea that is captured in this work is that soul continues to exist and takes a different body after the death. The primary goal of this work is to invent a new field titled "Artificial Soul Optimization (ASO)". The term "Artificial Soul Optimization" is coined in this paper. All the Optimization algorithms which are proposed based on Artificial Souls will come under "Artificial Soul Optimization" Field (ASO Field). In the Particle Swarm Optimization and Artificial Human Optimization, the basic entities in search space are Artificial Birds and Artificial Humans respectively. Similarly, in Artificial Soul Optimization, the basic entities in search space are Artificial Souls. In this work, the ASO Field concepts are added to Particle Swarm Optimization (PSO) algorithm to create a new hybrid algorithm titled "Soul Particle Swarm Optimization (SoPSO). The proposed SoPSO algorithm is applied on various benchmark functions. Results obtained are compared with PSO algorithm. The World's first Hybrid PSO algorithm based on Artificial Souls is created in this work.

Keywords: Artificial Souls, Artificial Soul Optimization, Artificial Soul Computing, Computational Intelligence, Evolutionary Computing, Particle Swarm Optimization, Genetic Algorithms, Artificial Human Optimization, Bio-Inspired Computing, Nature Inspired Computing, Machine Learning, Artificial Intelligence.

1 Introduction

The word Soul is present in sacred Hindu religious texts like Srimad Bhagavatham [1] and Bhagavad Gita [2]. “Soul Optimization” is something that deals with Real Souls. It can also be called as “Real Soul Optimization”. In this work, the focus is on Artificial Soul Optimization Field (ASO Field) which is defined in the abstract of this paper. Hence it is important to note that “Artificial Soul Optimization” and “Real Soul Optimization” are different.

The corresponding author asked, “Is there something like Soul Computing?” on Researchgate and an expert replied, “Just like I doubt you would find algorithms for ‘Unicorn computing’, I don't think you will find anything on ‘Soul computing’...”. Hence there is so much yet to be done in Real Soul Computing and Artificial Soul Computing fields.

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Nikola Tesla said, "The day science begins to study non-physical phenomena, it will make more progress in one decade than in all the previous centuries of its existence". Hence authors would like to suggest scientists to study and do projects related to non-physical phenomena like Real Soul Computing and Artificial Soul Computing. The current work studies Artificial Soul Optimization which comes under Artificial Soul Computing.

New ASO Field algorithms are created in this work by modifying Particle Swarm Optimization (PSO) algorithm with ASO Field concepts. Articles [3-9] give details related to PSO algorithms. Hybrid PSO Algorithms that are created by modifying PSO algorithm were shown in [10-14]. Hybrid PSO algorithms that are created by modifying PSO algorithm with Artificial Human Optimization (AHO) Field concepts and details related to AHO Field are given in articles [15-28]. There are no Artificial Soul Optimization Algorithms (ASO Algorithms) proposed in literature till date. Benchmark Functions used in this paper are taken from [29].

The rest of the article is organized as follows:

Section 2 shows Particle Swarm Optimization algorithm. Section 3 shows “Soul Particle Swarm Optimization (SoPSO)”. Results are explained in Section 4. Section 5 gives opportunities that are present in ASO Field. Section 6 gives Conclusions.

2 Particle Swarm Optimization

Particle Swarm Optimization (PSO) was proposed by Kennedy and Eberhart in 1995. PSO is based on Artificial Birds. It has been applied to solve complex optimization problems.

In PSO, first we initialize all particles as shown below. Two variables $pbest_i$ and gbest are maintained. $pbest_i$ is the best fitness value achieved by i^{th} particle so far and gbest is the best fitness value achieved by all particles so far. Lines 4 to 11 in the below text helps in maintaining particle best and global best. Then the velocity is updated by rule shown in line no. 14. Line 15 updates position of i^{th} particle. Line 19 increments the number of iterations and then the control goes back to line 4. This process of a particle moving towards its local best and also moving towards global best of particles is continued until termination criteria will be reached.

Procedure: Particle Swarm Optimization (PSO)

1) Initialize all particles
2) iterations = 0
3) **do**
4) **for** each particle i **do**
5) **If** (f(x_i) < f($pbest_i$)) **then**
6) $pbest_i = x_i$
7) **end if**
8) **if** (f($pbest_i$) < f(gbest)) **then**
9) gbest = $pbest_i$
10) **end if**
11) **end for**
12) **for** each particle i **do**
13) **for** each dimension d **do**
14) $v_{i,d} = w*v_{i,d} +$
$C_1*Random(0,1)*(pbest_{i,d} – x_{i,d})$
$+ C_2*Random(0,1)*(gbest_d – x_{i,d})$

15) $x_{i,d} = x_{i,d} + v_{i,d}$
17) **end for**
18) **end for**
19) iterations = iterations + 1
20) **while** (termination condition is false)

3 Soul Particle Swarm Optimization

The basic entities in Soul Particle Swarm Optimisation (SoPSO) are Artificial Souls. Each Artificial Soul corresponds to a point in search space. For the sake of simplicity, in this work we assume that there are two types of bodies that each Artificial Soul can take. The first body has Body Factor of BF1 and the second body has a Body Factor of BF2. In each generation, Artificial Souls take either first body or second body based on random number generated and BodySelectionProbability. If random number generated is less than BodySelectionProbability then first body is taken else second body is taken. In this study we took BF1 as 0.9 and BF2 as 0.1. Hence if Artificial Soul takes first body then it moves faster in search space because BF1 is 0.9. Whereas if Artificial Soul takes second body it moves slower in the search space because BF2 is 0.1. In each generation, body is dead after velocity and position are updated. Hence Artificial Soul takes new body in next generation. So the Artificial Soul remains eternal in all generations whereas the bodies taken are dead and a new body is taken in every generation by Artificial Souls.

In line number 13, a random number is generated and compared with BodySelectionProbability. If random number is less than BodySelectionProbability then the Soul takes first body else it takes second body. If first body is selected by Soul then lines 14-17 are executed and body factor BF1 is used in the position update equation. If second body is selected then lines 19-22 are executed and body factor BF2 is used in the position update equation. After velocity and position updates, the body taken by Soul is dead. This is the procedure shown for first generation and first Soul. The same procedure is repeated for all the Artificial Souls in first generation. Hence after velocity and position updates, all bodies taken by Souls are dead. Now the second generation is started and Souls take bodies based on random number and BodySelectionProbability as shown in line number 13. The remaining procedure is same as that of first generation. This process continues until termination criteria will be reached.

Procedure: Soul Particle Swarm Optimization (SoPSO)

1) Initialize all particles
2) iterations = 0
3) **do**
4) **for** each particle i **do**
5) **If** (f(x_i) < f($pbest_i$)) **then**
6) $pbest_i = x_i$
7) **end if**
8) **if** (f($pbest_i$) < f(gbest)) **then**
9) gbest = $pbest_i$
10) **end if**
11) **end for**
12) **for** each particle i **do**
13) **if** (rand(0,1) <BodySelectionProbability) // Soul takes first body
14) **for** each dimension d **do**
15) $v_{i,d} = w*v_{i,d} +$

```
                                      C1*Random(0,1)*(pbest_i,d – x_i,d)
                                    + C2*Random(0,1)*(gbest_d – x_i,d)
                              x_i,d = x_i,d + BF1* v_i,d
                    end for
          else // Soul takes second body
                    for each dimension d do
                              v_i,d = w*v_i,d +
                                      C1*Random(0,1)*(pbest_i,d – x_i,d)
                                    + C2*Random(0,1)*(gbest_d – x_i,d)
                              x_i,d = x_i,d + BF2* v_i,d
                    end for
          end if
     end for
     iterations = iterations + 1
while ( termination condition is false)
```

4 Results

The proposed Soul Particle Swarm Optimization (SoPSO) is applied on five benchmark functions. Results obtained are compared with PSO.

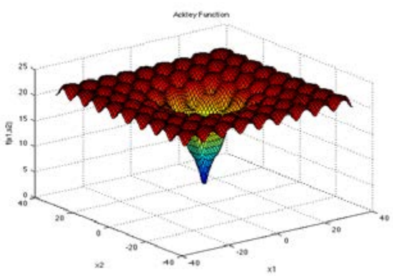

Figure 1. Ackley Function

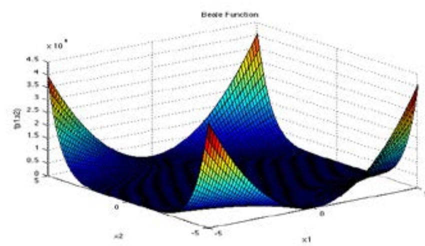

Figure 2. Beale Function

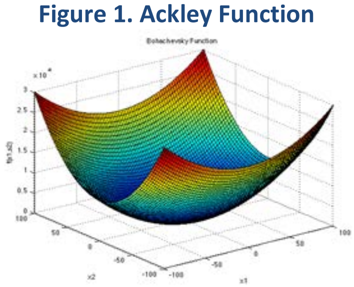

Figure 3. Bohachevsky Function

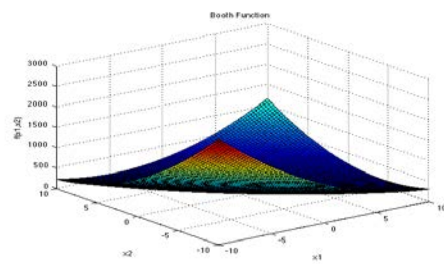

Figure 4. Booth Function

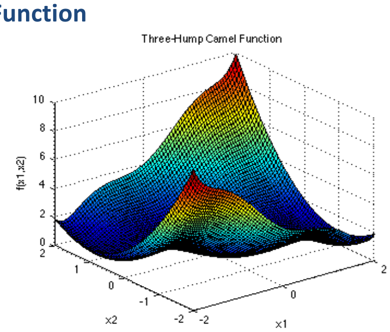

Figure 5. Three-Hump Camel Function

Table 1. Overall Result

Benchmark Function / Algorithm	SoPSO	PSO
Ackley Function		
Beale Function		
Bohachevsky Function		
Booth Function		
Three-Hump Camel Function		

In Table 1 Green represents Performed well. Red represents didn't performed well. Blue represents performed between well and not well. From Table 1 we can see that both SoPSO and PSO performed well on all benchmark functions.

5 Interesting Opportunities in Artificial Soul Optimization Field

The following are opportunities for experts in Computational Intelligence Field:

1) International Institute of Artificial Soul Optimization, Hyderabad, INDIA

2) Indian Institute of Technology Roorkee Artificial Soul Optimization Labs, IIT Roorkee

3) Foundation of Artificial Soul Optimization, New York, USA.

4) IEEE Artificial Soul Optimization Society

5) ELSEVIER journals in Artificial Soul Optimization

6) Applied Artificial Soul Optimization – A New Subject

7) Advanced Artificial Soul Optimization – A New Course

8) Invited Speech on "Artificial Soul Optimization" in world class Artificial Intelligence Conferences

9) A Special issue on "Artificial Soul Optimization" in a Springer published Journal

10) A Seminar on "Recent Advances in Artificial Soul Optimization" at Technical Festivals in colleges

11) International Association of Artificial Soul Optimization (IAASO)

12) Transactions on Artificial Soul Optimization (TASO)

13) International Journal of Artificial Soul Optimization (IJASO)

14) International Conference on Artificial Soul Optimization (ICASO)

15) www.ArtificialSoulOptimization.com

16) B.Tech in Artificial Soul Optimization

17) M.Tech in Artificial Soul Optimization

18) PhD in Artificial Soul Optimization

19) PostDoc in Artificial Soul Optimization

20) Artificial Soul Optimization Labs

21) To become "Father of Artificial Soul Optimization" field

6 Conclusions

A new field titled "Artificial Soul Optimization (ASO)" is invented in this work. A new algorithm titled Soul Particle Swarm Optimization (SoPSO) is designed and results show that proposed SoPSO performed well on all benchmark functions like PSO. In this work, a list of opportunities in ASO Field is shown for Computational Intelligence Field Experts. Not much work was done in Soul Computing and Artificial Soul Computing Fields till date. The new ASO field invented in this work comes under Artificial Soul Computing Field. There is scope for other innovative algorithms like Soul Ant Colony Optimization (SoACO) similar to SoPSO.

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