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Convolutional Neural Network with Random Uniform Weight Initialization for Salt Production Identification

N. Bala Vignesh[1] and Dr. V. Joseph Peter[2]

[1]Research Scholar, Research Department of Computer Science, Kamaraj College, Affiliated to ManonmaniamSundaranarUniversity,Thoothukudi

[2]Associate Professor, Research Department of Computer Science, Kamaraj College, Affiliated to ManonmaniamSundaranar University, Thoothukudi

Abstract

This research work develops CNN with a random uniform weight initialization method for salt production identification. In this research, the salt information present in the dataset is first divided into testing data (75%), and training (25%). The training samples are processed using CNN with a random uniform weight initialization algorithm to extract features automatically. The outcome of these extracted features is fed into softmax classification for predicting production class labels. After training, the learnable parameters and trained model are processed on the testing data to validate the proposed method performance. The performance of this proposed CNN with random uniform weight initialization method is evaluated using Accuracy, Recall, F1-score and Precision values. Thus, this method achieves 86% of accuracy, 91% of F1-Score, 91% of Recall and 91% of precision values. These results are further compared with the Multi-Layer Perceptron (MLP), K-Nearest Neighbor and Naive Bayes architecture.

Key Words: Salt Production identification, Convolutional Neural Network (CNN),Random Uniform Weight Initialization, Deep Learning, Artificial Intelligence.

1. INTRODUCTION

Salt is highly useful to preserve and flavor the food. The excessive salt intake may lead to osteoporosis, chronic kidney disease, cardiovascular diseases, and cancer (Lucarini et al. 2021). The salt substance is available in many forms. Himalayan pink salt is pink in color that helps to promote healthy PH, reducing muscle cramps and assist function in our body (Fayet-Moore et al., 2020).Sea salt, Celtic grey salt,fleur de sel salt, and Kosher salt are produced by the evaporation of sea or ocean water in which the salt product is harvested from the top layer of sea ponds. The purified form of sea salt is called table salt. The smoked salt is prepared by smoking sea salt at low temperature to add an additive flavor to the salt crystals. It contains fewer nutrients than the normal sea salt. Hawaiian sea salt is formed from the natural solar evaporation that is collected from the shallow clay ponds. The unrefined salt harvested from sea water near Hawaiian island is called Red Hawaiian Island.

Mostly, the salt product is harvested through the evaporation of sea water by salt miners. In this, the water is filled into the salt pans and then salt crystalline is formed by the evaporation of filled water. Before harvesting, the excess water is removed from salt pans (Iwuchukwu et al., 2018). The salt formation is highly dependent on the climate condition, which suffers from unexpected rains after or before the production started, this varies throughout the year based on climate changes (Eubanks et al., 2016).

The production quantity identification from the weather information will help us to improve the business of the salt miners. To achieve this task, the salt dataset is prepared using climate and production information from eleven different salt pans in Tuticorin district, Tamilnadu, India. Tuticorin is the second largest salt producer in India (AnanthaLaxmi R and Jeyakumari M, 2016). These data collected salt pans are SathyaMatha (SM), RSN salts, Tuticorin Salt & Marine Chemical Ltd (TMC), Alagar Salts (AS), Mannariah& Sons Tuty (MST), Rama Chandran (RC) salts, Shree Meenakshi Salt (SMS), PrammaSakthithi (PS) salts, Tuticorin Alkali Chemical Ltd (TAC), SK salt pan, and Velavan Salts (VS). Ten years of data are collected from these salt pans.

This research work developed the CNN with random uniform weight initialization method to identify the eight production class labels from salt informatics. The CNN network is easily able to find the specific patterns in a given input (Huang et al., 2017). This work is categorized into following three subsections: the related salt production identification methods discussed in section 2; experimental methodology of CNN with random uniform weight initialization method is detailed in section 3; experimental results and their comparison with existing methods are explained in section 4 and the conclusion of this proposed work has been detailed in section 5.

2. RELATED WORKS

The identification of salt production is difficult task because very limited works of similar research are available. Guntur et al. (2018) developed production of salt using the greenhouse method, which is the combination of threaded filter, geomembrane and prism greenhouse method. Hero et al. (2015) developed a novel salt production making process by adjusting the seawaterconcentration. These methods are able to detect salt from seismic images. But, the salt production identification from weather information at an early stage is still challenging in manufacturing industries.

The classification of class labels is traditionally addressed using many machine and deep learning methods (Chahal A and Gulia P, 2019). Decision tree is the machine learning based algorithm using tree like structure in which predicted class labels are represented in the leaf nodes. The computational power is high in decision tree based algorithms. The SVM method performs well in both binary and multi label classification, which contains very lesser performance on noisy data (Ali et al., 2018).

The CRF and MRF methods contain very limited performance on very small and real time data. The random forest classification method combines many small classifiers for providing solutions for the complex problems (Benard et al., 2021). It requires more time and more resources than the decision tree algorithm. The KNN and Naïve Bayes algorithms require high programmer interaction for initial seed value selection in the salt production identification process.

To overwhelm these limitations, the Artificial Neural Network (ANN) based algorithms are proposed to classify the patterns in raw data without the use of specific input features(Abiodun et al, 2018). The ANN based unsupervised self-organizing map algorithm contains volatile performance on real-time dataset. The Multi Layer Perceptron (MLP) based salt production identification algorithm needs a large number of parameters in which every perceptron have been connected with other parameters. It contains the redundant information in neural network layers.

Recently, the deep neural network methods are most suitable for classification problems; it avoids traditional hand-crafted features (Kaluarachchi et al., 2021). Alhusain et al. (2013) and Saii MM, (2019) suggested Artificial Neural Networks (ANN) and Deep Learning methods respectively for learning high-level features in an incremental manner. Yungii et al. (2018) implemented CNN based approach for salt body identification in seismic images. This method is capable to capture salt features automatically without the requirement of input features. Aleksandar has identified the salt deposits on seismic images using deep CNN based learning process, which is used to classify salt or non-salt seismic images (Aleksandar M, 2020).

To mitigate the existing drawbacks, the CNN with random uniform weight initialization method is trained and tested to identify the eight production class labels from salt informatics. The Layers in CNN are connected partially or sparsely rather than fully connected (Jegou et al., 2017). The CNN network is easily able to find the specific patterns in a given input (Huang et al., 2017). This CNN method achieves higher precision values when compared to the Naive Bayes, K-Nearest Neighbor and MLP architecture.

3. PROPOSED METHODOLOGY

The accurate prediction of production from salt mines is a challenging task because of the diverse nature of climate data present in the salt dataset. So, an efficient algorithm is necessary to identify the salt production, which helps to improve the manufacturing in salt mining industries. This research work proposes CNN with a random uniform weight initialization algorithm to extract and classify the salt features automatically from the input salt dataset. This proposed method is capable of capturing the specific patterns in a given input data. This methodology is majorly organized into four phases: workstation and database; and salt production identification using CNN with random uniform weight initialization method.

3.1. Workstation and Database

The CNN with random uniform weight initialization method is implemented using Intel R-corei7-4500Uprocessor, working underpython 3.8 version. The salt dataset is collected from eleven salt mining pans from Tuticorin district of Tamilnadu state in India. The climate and production details are collected from these salt pans for every month from the year from 2011 to 2020. The collected details are brine degree, minimum temperature, minimum humidity, maximum temperature, maximum humidity, wind speed, rainfall, wind direction, pressure,area, and total production. The dataset is composed of following eight class labels. Zero ton production - Class 1, 1 to 500 tons of salt production - Class 2, 501 to 1000 tons of salt production - Class 3, 1001 to 1500 tons of salt production - Class 4, 1501 to 2000 tons of salt production - Class 5, 2001 to 2500 tons of salt productions - Class 6, 2501 to 3000 tons of productions - Class 7, and 3000 to 3500 tons of productions - Class 8.

3.2. Salt production identification using CNN with random uniform weight initialization

The salt information is classified using CNN with random uniform weight initialization for predicting salt production. The salt information present in the dataset is first divided into training (25%) and testing samples (75%). The CNN with random uniform weight initialization model is then trained using training samples and tested using testing samples to classify the eight salt production class labels. The overall workflow of this proposed method is presented in Fig. 1 and depicted in below subsections.

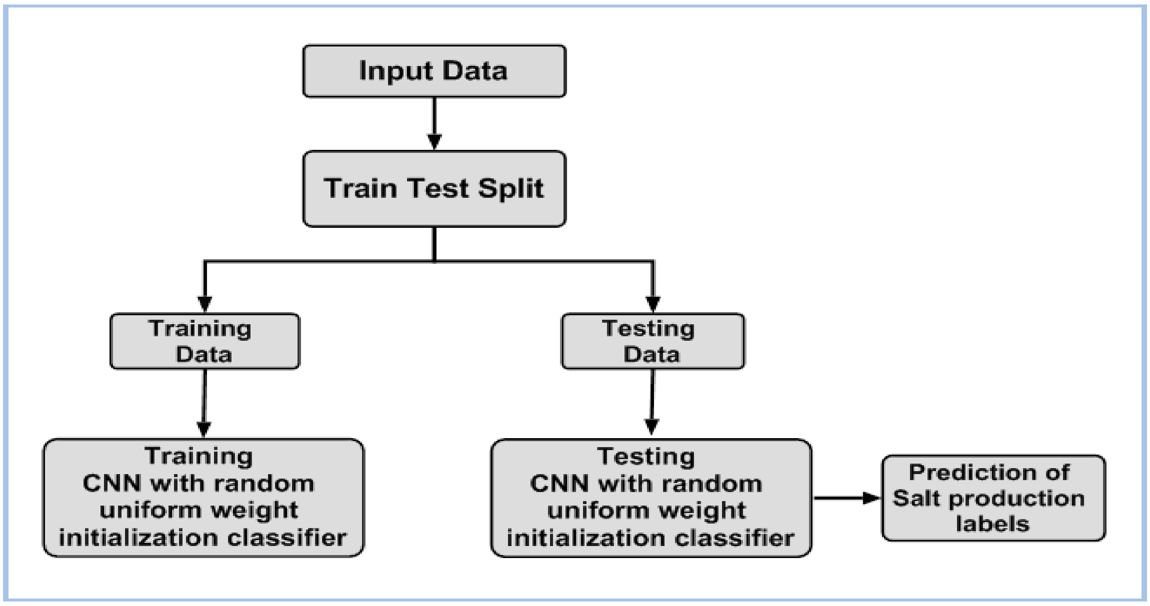

Figure 1: The workflow of CNN with random uniform weight initialization based salt production identification

The CNN with random uniform weight is used to extract production features automatically from salt dataset. The nodes present in the layers of this proposed network are connected partially or sparsely to one another. The proposed CNN based network is easily able to find the specific patterns in a given input. This network contains 1D (one Dimensional) convolution, one max pooling layer followed by FC and softmax layers. In this, all training input values are convolved using single dimensional kernels with random weights and bias to produce feature maps. The convolutional layer consists of shared weights of convolutional filters or kernels that slide over the input features and yields a manipulated outcome known as feature map. Here, an input image $x_j$is convolved with 1 x 1 kernel random weight w_i and bias value b_i to form feature map $y_i$is given in Eqn. (1).

$$y_i = f(\sum_{i=1}^{n}[x_i * w_i] + b_i) \qquad (1)$$

Where, *i=1,2,3…* n. This convolution layer is composed with two major parameters, like number of filters is equal to 64, kernel size, and stride value. The Rectifier Linear Unit (ReLU) activation function has been applied to non-linearly transfer the input vector into output features. There are different non-linear activation functions, namely hyperbolic tangent, sigmoid, and Leaky ReLU (Leaky Rectifier Linear Unit), Exponential Linear Unit (ELU), functions are available for transforming an input vector. But, the ReLU activation function contains faster convergence than the other functions (Maas et al., 2013). The formula for ReLU activation is defined in Eqn. (2).

$$ReLU(x) = max\ (0, x) \qquad (2) ReLU(x) = \begin{cases} 0 & If\ x < 0 \\ x & otherwise \end{cases}$$

After non-linear transformation, the feature map outcome is processed using 1D max-pooling for dimensionality reduction. The pool size is only the parameter of max pooling layer, in which a standard window of pool size is sliding over the feature map from convolution layer outcome (Nurbaity et al., 2020). The maximum value is calculated from this standard window for all the input values. The calculated value is replaced in every window in feature map values to get the dimensionality reduced outcome. It is mostly used to reduce the computational load of the CNN with a random uniform weight initialization network.

The softmax activation function has been applied to predict the probabilistic distribution of eight salt production class labels(Qiuyu et al., 2020). The outcome features from max pooling layer are converted as a single-dimensional array in the Fully Connected (FC) layer. It makes the one-to-one connection between the nodes in the previous layer to the next upcoming layer (Shabbeer Basha et al., 2019). The softmax activation function is further produced a number of salt class probabilities by interpreting input features.The proposed CNN with random uniform weight initialization architecture is visualized in Fig. 2.

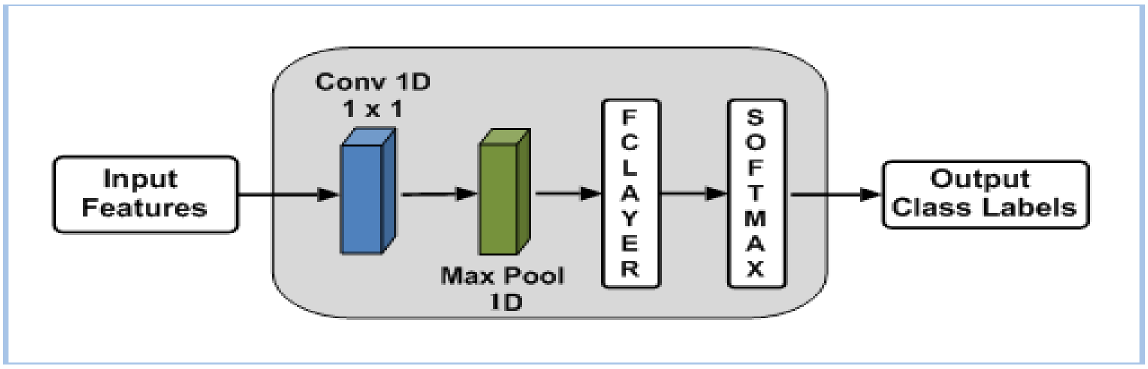

Figure 2: The architecture of CNN with random uniform weight initialization

These predicted production class labels are compared with original salt class labels for calculating an error. If this calculated error value is high then the network parameters are modified. After, all inputs are processed with these modified weights and bias values. The same process is computed again and again until the desired error value is minimal. The final modified weights and model are updated and saved. After training, the learnable parameters and trained model are processed on the testing data to predict the eight production salt class labels. This algorithm makes quicker predictions on testing data using the trained network parameters. The performance measurement over eight production class labels of this proposed algorithm is calculated using Accuracy, Recall, F1-Score, and Precision.

4. EXPERIMENTAL RESULTS AND COMPARISON

4.1.Efficiency of CNN with Random Uniform Weight Initialization

The effectiveness of CNN with random uniform weight initialization method is tested using salt production data that is collected from salt pans from Thoothukudi district. This deep learning based proposed method extracts features automatically from input salt data. The training and testing samples are first prepared from the dataset. This CNN method is used to convolve input data with weight and bias for extracting production features from salt data. Here, convolution with 1 x 1 kernels with weights and bias are used to extract features. The weights in the neurons of the convolution layer are initialized using the random uniform weight initialization method.

The max pooling is then applied to down sample feature dimensions of convolved features. This max poling outcome is converted as a single-dimensional array in the FC layer. The softmax classification technique is further processed over FC layer features to predict eight production class labels. The performance of CNN with random uniform weight initialization method over eight production class labels is detailed in Table 1. Fig. 3 and Fig. 4 show the performance chart and confusion matrix of the proposed CNN method. Thus, the CNN method achieves 86% of accuracy,91% of precision, 91% of Recall, and 91% of F1-Score.

Table 1: Performance of CNN with random uniform weight initialization method

Salt production data				
Method Name	**Accuracy value**	**Recall value**	**F1-Score value**	**Precision value**
CNN random uniform weight initialization	86	91	91	91

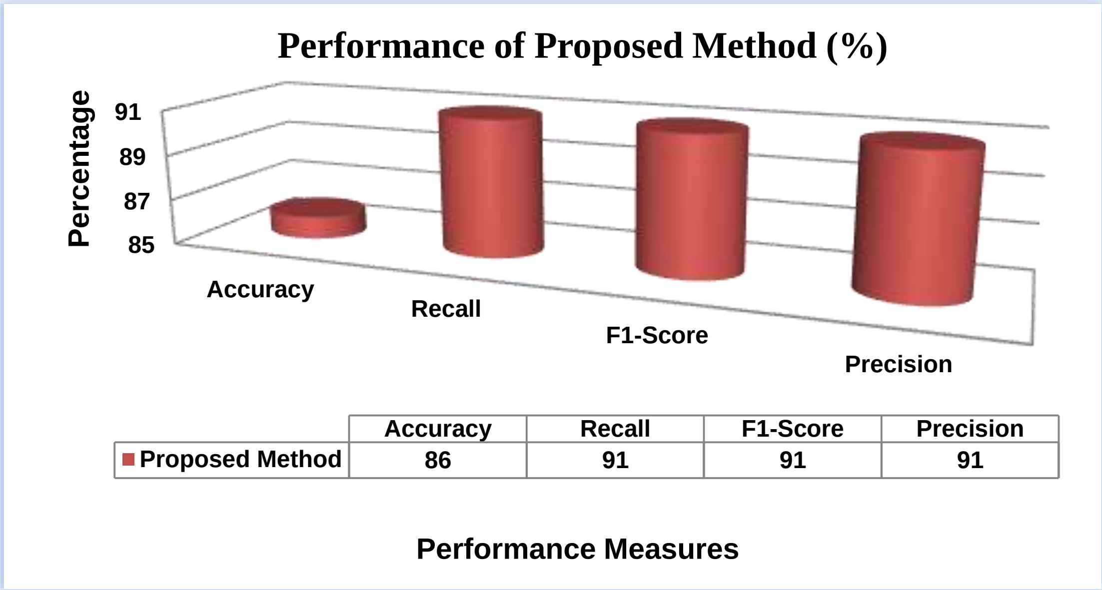

Figure 3: Performance chart of CNN with random uniform weight initialization method.

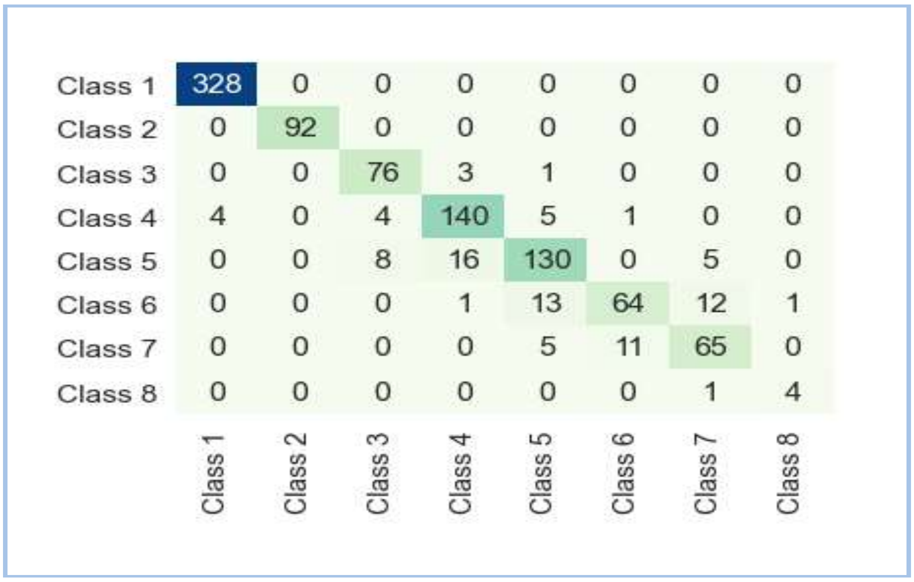

Figure 4: Confusion matrix of CNN with random uniform weight initialization method

4.2 Performance Comparison of CNN with Random Uniform Weight initialization method

The performance of CNN with random uniform weight initialization method is compared with the machine learning based Naïve Bayes, KNN and ANN based MLP methods. The KNN is the supervised algorithm that takes a long time to compute the classification results andits accuracy value is 72%, Precision value is 76%, Recall value is 72%, and F1-Score value 70%. The Naïve Bayes algorithm performs a salt production classification task using Bayes theorem, which achieves an accuracy value is 62%, Precision value is 64%, Recall value is 55%, and F1-Score value 62%.

To avoid these drawbacks, the ANN based MLP algorithm is processed over salt dataset to recognize and classify the patterns automatically from input data, which needs more parameters in which each perceptron has been connected with another perceptron as in the fully connected mode. The method achieves accuracy value is 83%, Precision value is 87%, Recall value is 85%, and F1-Score value 83%. It requires large computing power and high time consuming. To mitigate this limitation deep learning based CNN with random uniform weight initialization method has been proposed in this research. Which achieves an accuracy value is 86%, Precision value is 91%, Recall value is 91%, and F1-Score value 91%. Thus, the CNN with random uniform weight initialization method gained 3.6% higher accuracy, 7.1% higher recall, 9.6% higher F1-score, and 4.6% higher precision values when compared to the KNN, Naïve Bayes, and MLP algorithms. The performance comparison of CNN with random uniform weight initialization with KNN, Naïve Bayes, and MLP algorithms are presented in Table 2, and Fig. 5.

Table 2. The performance comparison of CNN with random uniform weight initialization method with the existing ANN methods

Salt production data					
S. No	**Method Name**	**Accuracy value (%)**	**Recall value (%)**	**F1-Score value (%)**	**Precision value (%)**
1	Naïve Bayes	62	62	55	64
2	KNN	72	72	70	76
3	MLP	83	85	83	87
4	**Proposed CNN with random uniform weight initialization**	**86**	**91**	**91**	**91**
Percentage increase in the Proposed Method		**3.6**	**7.1**	**9.6**	**4.6**

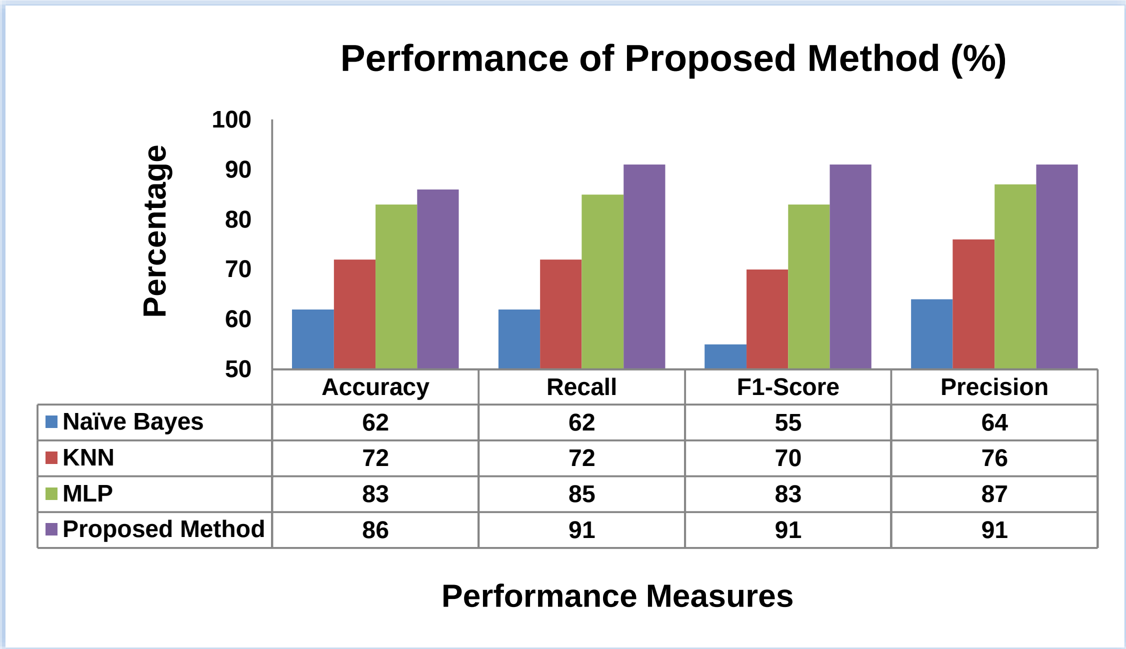

Figure 5: The performance comparison of **CNN with random uniform weight initialization method with existing CNN methods**

5. CONCLUSION

The prediction of production from salt dataset is a difficult and labor-intensive task. This research work developed CNN with a random uniform weight initialization method for automatic identification of production from salt informatics. In this method, the training and testing samples are prepared from the salt dataset. First, the training salt data is processed in the convolutional and pooling layers of the CNN architecture to extract the salt features automatically. The outcome of these extracted features is fed into softmax classification for predicting production class labels. After training, the learnable parameters and trained model are processed on the testing data to validate the proposed method performance. The CNN with random uniform weight initialization method achieves 86% of accuracy, 91% of precision, 91% of Recall, and 91% of F1-Score. Thus, this method gained 3.6% higher accuracy, 7.1% higher recall, 9.6% higher F1-score, and 4.6% higher precision values when compared to the KNN, Naïve Bayes, and MLP algorithms.

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