



REGULAR ARTICLE

AI-Driven Machine Learning Model for Stress Classification in Thin Film Materials

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In a range of practical applications, which contain microelectronics then aerospace engineering, the sorting of stress in thin film material is dynamic for maximizing their presentation and dependability. By integrating revolutionary data training methods with a unique classification, this study suggests an AI-driven Machine Learning (ML) method for stress classification in thin film material. To promise high-quality input for the knowledge of manner, the technique uses data cleaning strategies to cast off noise and outliers. Z-score normalization is used to standardize the data, expanding the technique's applicability to a wider variety of information. This study presents the Refined Crayfish Optimised K-Nearest Neighbor (RCO-KNN) algorithm for the enterprise job that is scheduled to raise the precision and resilience of strain detection in skinny movie materials. The RCO-KNN approach advances at the KNN by making use of Crayfish Optimization, which maximizes the selection of neighbors and distance metrics to guarantee accurate classification. This ROC-KNN achieved high accuracy (98.5 %), precision (96.2 %), recall (95.6 %), and F1-score (97.8 %). According to experimental results, this information gives a tremendously dependable tool for material science programs in guessing out the stress levels in thin film materials.

Keywords: Stress classification, Thin film materials, Refined Crayfish Optimised K-Nearest Neighbor (RCO-KNN), Z-Score normalization.

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1. INTRODUCTION

The process of stress classification entails determining and classifying many types and intensities of stress that materials undergo in diverse circumstances. This is important in predicting material behavior, preventing failures, and optimizing design in disciplines such as materials science and engineering [1]. Advanced techniques such as ML improve the performance and reliability of the materials, and with these, classification of stress can be done more precisely and rapidly [2]. Stress classification in thin film materials is all about the identification and classification of various kinds of stress that the materials undergo while they are produced and utilized, including tensile, compressive, and shear stress. In electronics, optics, and coatings, the thin films have to be classified precisely so that mechanical integrity and demonstration can be ensured. Material design and

dependability can be enhanced with enlarged accuracy and efficacy of stress analysis by using ML approaches refined for this kind of analysis [3]. Thin film materials are highly thin layers that have a definite chemical and physical characteristics. Typically, the thickness of the films varies between a few micrometres up to several micrometres. These materials have enormous applications in the fields of optics, electronics, and coatings. They are an essential part of the operation of a number of devices, from sensors and solar cells to semiconductors. Thin film growth and characterization is highly essential for the improvement of the skills that have a critical need for precision and accuracy [4]. The analysis of stress in AI driven thin-film materials applies sophisticated ML measurements that detect and classify accurately the different stress levels that might prevail in these high-tech materials. This novel methodology advances conventional analytical tactics for claims in coatings and electronics by

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having the capability of making it possible to provide more rapid and accurate insights on material performance. In stress testing, including AI can effectively reduce the risk of failure and improve the material's performance [5]. Residual stress is a material property of dropped layers of thin film used in the Nano system fabrication [6]. The use of these methods to classify different types and amounts of stress improves the performance of thin films used in various applications. These AI-driven methods highly advance material design and failure avoidance methods by automatically allowing for the prediction of stress [7]. As they can learn complex patterns from huge datasets, neural networks have become real tools in the classification of stress in thin film materials. They may dependably and precisely determine the stress level based on data coming from approaches. This strategy importantly advances the field of materials science as conventional analysis methods are refined together and enabled for real-time monitoring [8]. The objective is to advance the performance and dependability of materials by making an AI-driven ML method that properly detects the degrees of stress in thin-film materials.

2. RELATED WORKS

Sadowski (2022) proposed an auto-organization technique for a cylindrical shell nonlinear bifurcation buckling eigenmode: pipes, chimneys, silos, tanks, piles, and wind turbine support towers. The PyTorch ML framework is helpful as a foundation, and in order to validate the presentation of the classifier, there is employment of a parametric sweep of a cylindrical shell under asymmetrical wind loads [1].

Yang et al., (2021) suggested a technique to forecast the behavior of compound materials without regard to component forms. Geometric hierarchy and boundary conditions offered visions for carrying out simulations and physical modeling. The method significantly increased the efficiency of measuring the physical characteristics of hierarchical materials based on the geometry of their structural composition [9-10].

Badkul et al., (2020) suggested a way to forecast a closed-cell metallic foam experimental behavior in the compaction area. After adjusting the crushable foam method's additional input parameters, stress-strain material curves were evaluated to predict the compressive load-displacement properties of metallic foam based on experimental findings. It has been exposed that the way that metallic foam hardens can be described by engineering stress. Real strained values correctly predict its compressive behavior employing a method of crushable foam [11].

Lu et al., (2020) developed and frequently used instrumented indentation for obtaining a material's mechanical property. It was preferred difficult to obtain the mechanical characterization experimentally utilizing coupon specimen stress-strain information. Direct contrasts have been used to assess the benefits and predictive power of these multifidly methods [12].

3. METHODS AND MATERIALS

This study presents the novel Refined Crayfish Optimized K-Nearest Neighbor (RCO-KNN) approaches, which combine the KNN algorithm and optimize the RCO method for stress classification in thin film materials. Fig. 1 shows the flow of methodology.

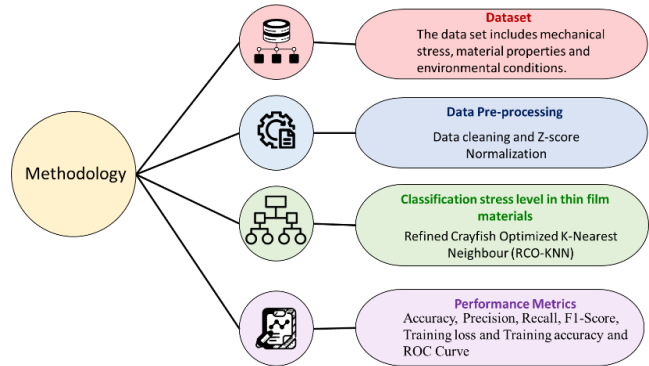


Fig. 1 – Flow of Methodology

3.1 Dataset

The study gathers mechanical stress measurements, material properties, environmental information, and material properties. Tensile and compressive stress levels under numerous situations are among the mechanical stress measurements included in the data. Besides recording material characteristics such as film thickness, it also records environmental parameters like humidity and temperature during stress testing [13].

3.2 Pre-processing

The study aims at classifying the stress level in thin film materials. Two pre-processing approaches were also used in this study for the collected data in the pre-processing phase-the Z-score Normalization and data cleaning.

3.2.1 Data Cleaning

Data cleaning has to find and correct erroneous data, high-quality inputs, inconsistencies, and the missing values of the set. Thin film material stress classification accuracy can be refined at. Data formats can now be standardized, and further outliers eliminated to make more professional learning by the algorithm from clean data.

3.2.2 Z-score Normalization

To standardize the data and guarantee consistent feature scaling for more precise stress classification in thin film materials, Z-score Normalization was used. The Z-score normalization plots a value from characteristic F to u' a range that was previously unlimited, which can be realized in Equation (1).

$$u' = \frac{u_j - F_j}{std(F)} \quad (1)$$

Where u' represents the outcome of the normalization value, u depicts the value to be normalized in the attribute, F_j is the mean value of the attribute, then $std(F) =$ standard deviation attribute F .

3.3 Refined Crayfish Optimized K-Nearest Neighbor (RCO-KNN)

In the feature selection, KNN parameters are dynamically combined with RCO to advance stress classification accuracy in thin film materials. This integration is in line with the study of improving material performance and dependability by means of accurate and effective stress classification.

3.3.1 K-Nearest Neighbour (KNN)

KNN is utilized to classify stress levels in thin film materials. A well-liked supervised ML method is the KNN method. To predict new data points, it takes advantage of the feature similarity attribute. The projected data points are assigned values according to which training set points they most closely match.

Since KNN effectively uses distance-based similarity metrics to classify stress levels in thin film materials. Classification accuracy is improved by its versatility and simplicity with dynamic optimization. Fig. 2 Architecture of KNN.

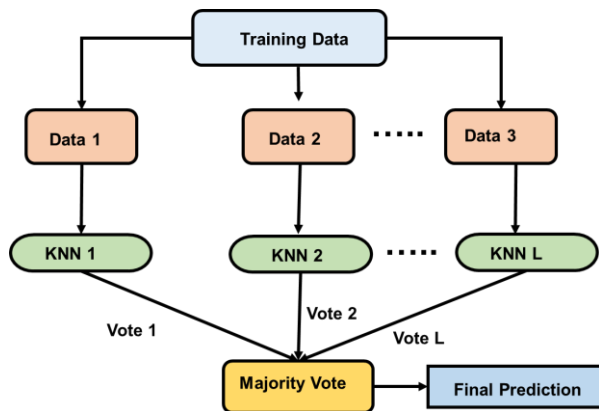


Fig. 2 – Architecture of KNN

- Compute the value of k , where k is the neighbor's closest value.
- Determine how far off the data point that wishes to categorize is from the training data points.
- Arrange the training data points in ascending order based on the distance values.
- Make a forecast based on the bulk of the closest neighbors.

As a result, the k value is from 2 to 9. It employs the uniform weight function to assign weights to the points. In each neighbor, every point is given the same weight by this function. It utilizes the Minkowski distance formula to determine the length of time. Between two variables, W

and Z , the Minkowski distance of order O can be expressed in Equation (2).

$$(\sum_{j=1}^m |W_j - Z_j|^O)^{\frac{1}{O}} \quad (2)$$

Where m is the variable's dimension number. The Manhattan distance is represented by $O = 1$, and the Euclidean distance by $O = 2$. In this system, it employs $O = 2$.

3.3.2 Refined Crayfish Optimization (RCO)

KNN parameters are dynamically optimized through the use of RCO, which improves model efficiency and the accuracy of stress categorization. A class of crustaceans renowned for their quick development, quick migration, and remarkable adaptability are crayfish, commonly referred to as red crayfish or freshwater crayfish. Temperature fluctuations have an impact on them and they do best in freshwater settings. They venture into caves to protect themselves from the heat when the weather is too hot, and they emerge to feed when the weather is right. The temperature has an impact on crayfish since they are ectotherms, and their range is 20 to 35 degrees Celsius. Equation (3) gives the calculation for temperature. Where $temp$ represents the surrounding crayfish temperature. The process of RCO optimization is represented.

$$temp = rand \times 15 + 20 \quad (3)$$

a) Commencing Population Initialization

In the RCO d -dimensional optimization problem, crayfish are 1×1 matrix solutions. Every item in a set of variables $(W_1, W_2, W_3, \dots, W_d)$ has a location (W) that falls within the search space's upper ub and lower lb boundaries. By computing and comparing, the algorithm determines, which answer is ideal. Through the use of Equation (4), the crayfish population is initialized.

$$W_{j,i} = lb_i + (ub_i - lb_i) \times rand \quad (4)$$

Where $W_{j,i}$ denotes the location of the j -th crayfish in the i -th element, ub_i denotes the upper bound of the i -th dimension, lb_i denotes the lower bound of the i -th dimension, and a $rand$ is a random number from 0 to 1.

b) Summer Retreat Period (Investigation Stage)

To determine whether the current living situation is in a high-temperature setting or not, a threshold temperature of 30 °C is used. To protect themselves from the damaging effects of high temperatures, crayfish seek cool, wet caves during the summer months when temperatures rise above 30 °C. Equation (5) is the calculation for the caves.

$$W_{shade} = (W_H + W_K)/2 \quad (5)$$

Where W_K denotes the ideal location of the current population and W_H is the optimal position found thus far

for this evaluation number. A random number is constructed to imitate the unpredictable nature of the crayfish competition for a cave. Currently, Equation (6) is used to calculate the updated position of crayfish.

$$W_{new} = W_{j,i} + D_2 \times rand \times (W_{shade} - W_{j,i}) \quad (6)$$

In this case, D_2 is a declining curve, and W_{new} is the position that comes after a location update. The equation (7) for D_2 is described as follows.

$$D_2 = 2 - (EF_T / MaxEF_T) \quad (7)$$

In this case, EF_T stands for the total number of evaluations, and $MaxEF_T$ for the highest possible number.

c) Competitive Phase (Application Phase)

Once the temperature surpasses 30 °C and the rand value is less than 0.5, it suggests that other crayfish compete with the crayfish for the cave during their summertime quest. The two crayfish will currently engage in combat with the cave, and crayfish W_j will move in reaction to where W_y is. Equation (8) is used to get the adjustment position. The equation (9) for the random individual computation.

$$W_{new} = W_{j,i} + W_{y,i} + W_{shade} \quad (8)$$

$$z = \text{round}(\text{rand} \times (M - 1)) \quad (9)$$

Where Z in this case stands for the crayfish's random person. M represents the size of the population.

d) Hunting Phase (Exploitation Stage)

Temperature affects crayfish foraging behavior; they need temperatures of at least 30 °C to be able to climb out of caverns and obtain food. Crayfish search for the best place to get food by drilling out of caves when the temperature is at or below 30 °C.

4. RESULT

The objective of the study is to generate a ML model powered by AI that can precisely categorize the stress levels in thin-film materials. To estimate the effectiveness of the proposed system, the following metrics are evaluated: recall, precision, accuracy, training and loss accuracy, F1-score, Training loss and training accuracy and ROC curve. Table 1 and Figure 3 show the result of the proposed method.

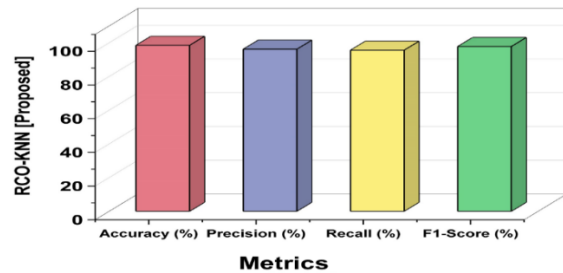


Fig. 3 – Result of proposed

Table 1 – Outcomes of the suggested method

Metrics	Values (%)
Accuracy	98.5
Precision	96.2
Recall	95.6
F1-score	97.8

Impressive outcomes are shown by the performance metrics for the suggested RCO-KNN approach. The model has a high degree of correctness in classifying cases within the dataset, with an accuracy of 98.5 %. The model's efficacy in recognizing actual positive situations is demonstrated by its 95.6 % recall and 96.2 % precision, which both reveal that a sizable number of its positive predictions are accurate. A great general performance is designated by the 97.8 % of F1-score, which attacks a balance between precision and recall. Together, these measures demonstrate the practical uses of the RCO-KNN method promise for efficient categorization.

4.1 Training Loss and Training Accuracy

Training loss refers to the error or difference between the forecast output of a method and the actual target during the work. Training accuracy measures how often the model correctly predicts the target values during the training process. Accuracy of training and loss graphs are used to show how well the suggested model performs. In this case, the x-axis represents the number of model training epochs, or training cycles, across the entire dataset, while the y-axis represents the accuracy and loss, respectively. Fig. 4 depicts the outcomes of training and loss of accuracy.

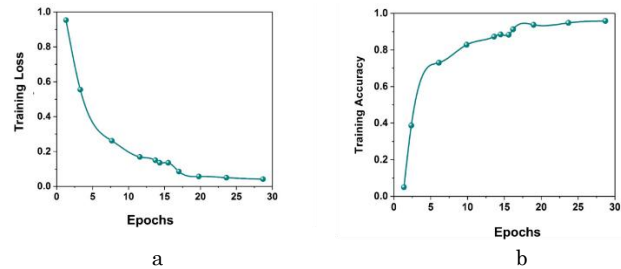


Fig. 4 – Result of Training and loss of accuracy

The RCO-KNN model's training results across a number of epochs are shown in the graphs. As the model reduces errors, the accuracy loss in graph (a) dramatically drops from almost 1.0 to almost 0.0 during the first epochs, suggesting successful learning. Graph (b) indicates that the model attains a high degree of prediction accuracy as training goes on, with the training accuracy rising gradually and stabilizing close to 1.0. Collectively, these patterns show how the model can effectively lower loss while quickly enhancing performance throughout training.

4.2 Receiver Operating Characteristic Curve

A graphical tool for assessing a binary classification model's performance is a ROC curve. At different

threshold values, it shows how the true positive rate and false positive rate are traded off. The ROC curve is frequently used to assess the performance of several models and choose the ideal threshold for classification in a variety of domains. Fig. 5 illustrates the ROC curve.

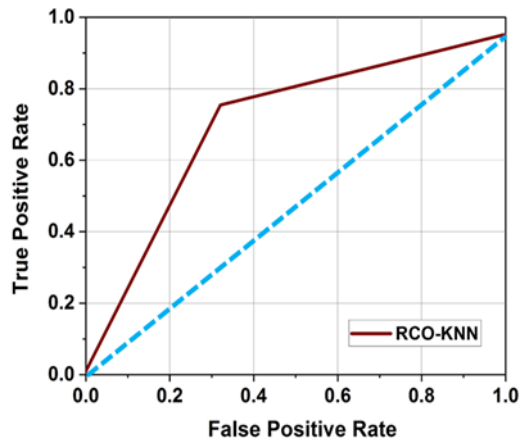


Fig. 5 – Result of ROC Curve

The ROC curve demonstrates the performance of the RCO-KNN method in stress classification of thin film materials. The value 0.085 indicates that a true positive rate of ROC.

5. CONCLUSION

The objective of the study is to produce an AI-powered ML method for the strain classification of thin-film materials. The method pursues to advance accuracy and efficiency over conventional approaches by automating stress detection using sophisticated algorithms. This technique advanced material dependability in sensors, electronics, and optics applications. High accuracy (98.5 %), prediction (96.2 %), recall (95.6 %), and F1-score (97.8 %) were achieved by the RCO-KNN technique for the classification of stress in thin-film materials. Furthermore, advanced hybrid AI approaches can boost prediction efficiency and accuracy in a variety of industrial applications. The RCO-KNN approach's drawback is its dependence on the quality and quantity of training data, since incomplete or skewed data may result in incorrect stress classifications. Furthermore, the Crayfish Optimization process's processing complexity can limit its use in situations requiring prompt decision-making.

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Модель машинного навчання на основі штучного інтелекту для класифікації напружень у тонкоплівкових матеріалах

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У низці практичних застосувань, що включають мікроелектроніку та аерокосмічну техніку, сортування напружень у тонкоплівкових матеріалах є динамічним для максимізації їх представлення та надійності. Інтегруючи революційні методи навчання даних з унікальною класифікацією, це дослідження пропонує метод машинного навчання (ML) на основі штучного інтелекту для класифікації напружень у тонкоплівкових матеріалах. Щоб гарантувати високоякісний вхідний сигнал для знань про тип, метод використовує стратегії очищення даних для видалення шуму та викидів. Нормалізація Z -оцінки використовується для стандартизації даних, розширюючи застосовність методу до ширшого кола інформації. Це дослідження представляє вдосконалений алгоритм Crayfish Optimised K-Nearest Neighbor (RCO-KNN) для корпоративного проекту, який має підвищити точність та стійкість виявлення деформацій у тонкоплівкових матеріалах. Підхід RCO-KNN розвивається в KNN, використовуючи Crayfish Optimization, яка максимізує вибір сусідів та метрик відстані для гарантії точної класифікації. Цей ROC-KNN досяг високої точності (98,5 %), прецизійності (96,2 %), повноти (95,6 %) та F1-оцінки (97,8 %). Згідно з експериментальними результатами, ця інформація є надзвичайно надійним інструментом для програм матеріалознавства для визначення рівнів напружень у тонкоплівкових матеріалах.

Ключові слова: Класифікація напружень, Тонкоплівкові матеріали, Алгоритм Crayfish Optimised K-Nearest Neighbor (RCO-KNN), Нормалізація Z -оцінки.