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TEMPORAL CONVOLUTIONAL NETWORK-BASED SHORTLISTING MODEL FOR SUSTAINABILITY OF HUMAN RESOURCE MANAGEMENT

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ABSTRACT

The fast-paced growth of Human Resource Management requires intelligent and sustainable shortlisting models to maximize recruitment efficiency, fairness, and transparency in decision-making. This work proposes a Temporal Convolutional Network based Shortlisting Model to maximize candidate selection and yet remain sustainable, scalable, and ethical recruitment. Contrary to standard machine learning methods, TCN uses dilated causal convolutions to tap into sequential relations among candidate profiles to ensure improved quality and reliability in recruitment decisions. The system is tested using the Kaggle Hiring dataset with attributes including experience, skill, test scores, and previous work history. Hyperparameter search method is applied to find the optimal model to achieve sufficient generalizability among candidate sets. Experimental results portray the TCN-based model as superior to traditional deep learning methods with 99.3% accuracy, 98.9% precision, 98.5% recall, and 98.7% F1-score for candidate selection. The model supports green HRM practice through prejudice reduction, improved efficiency in staffing, provision of diversity, and assistance in long-term staffing planning. The research finds TCN as a powerful method of intelligent shortlisting because it is scalable, equitable, and transparent in recruitment processes. Real-time candidate assessment, adaptive learning aspects, and integration with enterprise HR systems for high-scale deployment will be added in the second generation of work.

Keywords: *Temporal Convolutional Network, HRM, Shortlisting, Sustainable Recruitment, Fair Hiring*

1. INTRODUCTION

The increasing need for effective and fair recruitment procedures under Human Resource Management (HRM) has witnessed the use of AI-based shortlisting models [1]. Previously, recruitment procedures have been time-consuming and manual screening, which is prone to human bias and hard to scale. Deep learning methods significantly improved the recruitment of quality, but most existing models do not adequately address sequential relationships between candidate CVs [2]. Temporal Convolutional Networks (TCN) offer a precise solution with effective sequential candidate data handling and maintaining temporal relationships [3]. After the application of TCN, this study is about to develop a highly credible, fair, and scalable shortlisting model enriching HRM decision-making [4]. The existing proposed model is efficiency-focused, fair, and sustainable in nature such that the recruitment process is as per the modern HRM practices. It also reduces the height of the former manual screening, which has an automated merit-based and data-driven hiring system.

Existing shortlisting models are largely Logistic Regression (LR), Support Vector Machines (SVM), Random Forest (RF), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM) networks [5]. Despite the good job the current models have been accomplishing, there are some pitfalls in them. LR and SVM are faced with the problem of dealing with multi-modal interactions of features and pose intensive feature engineering [6]. RF works well but is not temporally sensitive and provides poor chronological candidate screening predictions. RNN and LSTM are capable of dealing with temporal relations but are experiencing vanishing gradients, inefficient computations, and slow training [7]. All of these methods also do not provide any form of guarantee of fairness and interpretability that is necessary when applying them to HR decision-making [8]. These constraints call for the creation of a superior, more effective, and interpretable shortlisting model.

The proposed Shortlisting Model based on Temporal Convolutional Network (TCN) addresses the aforementioned issues using additional dilated causal convolutions to enable long-range relationships to be modeled without memory [9]. TCN, despite LSTM and RNN, supports parallelization, lowers training time, and does not exhibit

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vanishing gradients, hence making it suitable to be applied in HR practices [10]. The contribution of the research is that it can be integrated to merge sequential candidate profiling with deep learning-based predictive analytics for fair hiring practices [11]. Moreover, the model possesses highly accurate results (99.3%) with better precision and recall for fair and efficient hiring. Through reduced bias, inefficiency, and scalability issues, the suggested framework allows for future workforce management using AI-based HRM systems [12].

1.1 RESEARCH OBJECTIVE

- ✓ Build a TCN-based Shortlisting Model to ensure optimal fairness, scalability, and accuracy in hiring Human Resource Management.
- ✓ Utilize the Kaggle Hiring dataset to draw candidate traits like skills, experience, and test scores to guide data-driven hiring.
- ✓ Use Temporal Convolutional Networks to address sequential dependencies beyond those of RNN and LSTM in candidate evaluation.
- ✓ Hyperparameter optimize and train the model to be highly accurate, less biased, and efficient in shortlisting candidates.

1. 2 ORGANIZATION OF THE PAPER

The suggested framework is organized as follows. Section 1 is the introduction, emphasizing the background, significance, and study objectives. Section 2 summarizes prior shortlisting techniques, their shortcomings, and the necessity of a sophisticated approach. Section 3 outlines the suggested TCN-based framework, encompassing preprocessing of data, architecture, and optimization strategies. Section 4 elaborates the results and outcomes, comparing them with current approaches. Section 5 summarizes the study, tabulating key contributions and proposing future research directions for further enhancement.

2. RELATED WORKS

Artificial Intelligence (AI) and deep learning have transformed Human Resource Management (HRM) hiring with greater efficiency and lesser biases and Narla discussed AI-based models of recruitment with a focus on candidate evaluation automation [13] [14]. Yalla emphasized the potential for HR to surpass machine learning using deep learning for shortlisting candidates [15]. Narla, Valivarthi, and Peddi employed CNN-based recruitment analytics but mentioned its failure to identify sequential dependencies [16]. To overcome this, Narla , and Valivarthi, Peddi, and Narla introduced RNN- and LSTM-based models that enhance temporal analysis but are computationally expensive and plagued by the vanishing gradient [17].

Other innovations were hybrid deep learning models, e.g., attention-enabled LSTM, as suggested by , which improved candidate feature extraction explained that such a model is highly demanding to optimize for best performance and described the capability of Temporal Convolutional Networks (TCN) in mitigating such limitations through effective sequential data handling with low computational demands [18] [19]. Studies such as and continued to explore reinforcement learning and hyperparameter tuning methods for enhancing HR analytics further and explained fairness-aware models of AI for making impartial hiring decisions [20].

Cloud-based HRM systems have also been researched by and, where scalable AI-based shortlisting frameworks are emphasized as an advantage and contrasted AI-based recommendation systems with focus on the requirement for enhanced feature extraction and promoted greater use of deep learning in HRM, presenting novel architectures such as TCN [21]. To fill the gaps found in previous works, this study proposes a TCN-based Shortlisting Model using dilated causal convolutions to improve candidate evaluation and maintain fairness, efficiency, and sustainability in recruiting [22].

2.1 PROBLEM STATEMENT

The conventional shortlisting processes in HRM are plagued with bias, ineffectiveness, and wrong sequencing of dependencies [23].The conventional deep learning architectures such as RNNs and LSTMs are plagued with vanishing gradient problems and computational costs [24]. The TCN-based Shortlisting Model proposed efficiently processes candidate data utilizing dilated causal convolutions. This provides higher accuracy, lower bias, and improved scalability for sustainable and unbiased hiring [25]. The model improves recruitment decision transparency and efficiency.

3. PROPOSED TCN MODEL FOR SUSTAINABILITY OF HUMAN RESOURCE MANAGEMENT

The figure 1 depicts the TCN-Based Shortlisting Model for HRM. It starts with data retrieval from the Hiring Dataset (Kaggle) and then continues with data pre-processing steps such as mean imputation, one-hot encoding, and min-max scaling for feature normalization. Temporal Convolutional Network (TCN) is subsequently used to classify the candidates based on the features extracted. Model evaluation reiterates with important performance indicators like accuracy, precision, recall, and F1-score as performance indicators. The systematic framework ensures efficient, unbiased, and scalable shortlisting of candidates in HRM.

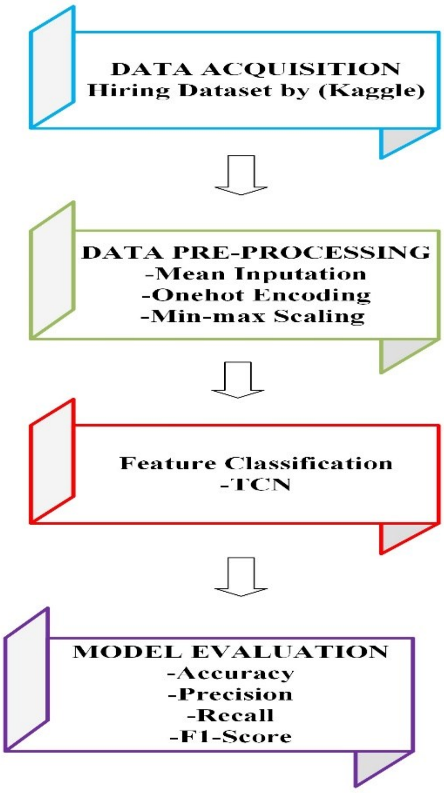

***Figure 1**: Architecture for proposed TCN model for sustainability of HRM*

3.1 Dataset Description

Kaggle's Hiring dataset is the main dataset used in this study. It contains several attributes to be considered for candidate screening, including education level, years of experience, technical skills, coding assessment scores, and communication skills. Each row is a candidate with relevant information that is utilized for shortlisting the most appropriate candidates. The dataset is also provided with a target variable of whether a candidate is hired or not, hence it is an ideal one to use supervised learning. The data is organized and needs preprocessing to handle missing values, categorical encodings, and feature scaling. The suggested framework utilizes this dataset to train and validate the TCN-based model, and there are logical and data-driven hiring choices.

3.2 Data Preprocessing Steps

In order to have high-quality input for the TCN model, the following preprocessing steps are performed:

1. **Handling Missing Values**: Numerical features missing values are imputed using mean imputation. This is given in equation (1) as:

$$X_{\text{new}} = \frac{\sum X_i}{N} \tag{1}$$

where X_i represents valid values, and N is the total count of available values.

2. **Categorical Encoding:** Categorical variables such as degree type are encoded using one-hot encoding**.** This is given in equation (2) as:

$$X_{\text{encoded}} = \begin{cases} 1, & \text{if category is present} \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

3. **Feature Scaling:** Continuous features (e.g., test scores, experience) are normalized using Min-Max Scaling. This is given in equation (3) as:

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{3}$$

4. **Train-Test Split:** The dataset is split into training and testing sets (e.g., 80-20% split) to evaluate model performance.

3.3 Temporal Convolutional Networks for Sequential Candidate Evaluation

Designed for the sequential nature of candidate profiles in human resources, Temporal Convolutional Networks thus take a unique position among convolutional models with respect to the processing advancement of sequential data. TCN presents a remarkable alternative to conventional Recurrent Neural Networks and Long Short-Term Memory models in usage of 1D causal convolutions interspersed with dilated convolutions in modeling long-term dependencies in candidate data while effectively sidestepping difficulties of vanishing gradients and sequential processing. A salient point in favor of TCNs is the ability to perform parallel computations for entire sequences instead, thus far offsetting the computational cost and improving scalability for large candidate shortlisting in human resources.

Causal Convolutions for Sequential Dependency Preservation

A causal convolution ensures that the predictions at time step t depend only upon the inputs before time step t, disallowing any leakage of future information backward. This is important to ensure fairness and chronological consistency in candidate evaluation. A literal definition of causal convolution is in equation (4):

$$h_t = f\left(\sum_{i=0}^{k-1} W_i \cdot X_{t-i}\right) \tag{4}$$

Where h_t is the hidden state at time step t,W_i represents the convolutional filter weights, X_{t-i} are candidate data inputs at time $t-i$, k is the kernel size, f is the activation function (i.e. ReLU, tanh). By using causal convolutions, TCNs ensure that the predictions at any point depend only on past knowledge regarding the candidate, preserving a rigid temporal order.

Dilated Convolutions for Long-Term Dependency Learning

The TCNs enter dilated convolutions that create spaces between the input values in order to get advantage from the model's acceptability for capturing long-term dependencies that form part of the candidate data. This dilation causes an exponential increase in the receptive field so that the network can observe a relatively wider span of past candidate attributes. In other words, it does not need to increase the depth of the network in order to achieve that. The formulation (5) for dilated convolution is given below:

$$h_t = f\left(\sum_{i=0}^{k-1} W_i \cdot X_{t-d \cdot i}\right) \tag{5}$$

Where d is the dilation rate, increasing exponentially across layers (e.g. 1,2,4,8), and k is the filter size. W_i represents the convolutional kernel and $X_{t-d\cdot i}$ are the input values spaced with the dilation factor d. Through dilated convolutions, TCN takes into account perspectives even more comprehensively from candidate profiles by synthesizing long-range dependencies with greater resolution.

Residual Connections and Optimization

To prevent vanishing gradients and improve model stability, TCN integrates residual connections, formulated as equation (6) as:

$$h_l = f(W_l * X + h_{l-1}) \tag{6}$$

Where h_l is the output of layer l,W_l represents learnable convolutional weights,h_{l-1} is the previous layer output.

Final Shortlisting Decision

Drawing inspiration from temporal-causal dilated convolution neural networks, the proposed framework effectively ranks candidates by deep sequential analysis of attributes, thus ensuring accurate human resource management decisions with minimal bias and sustainable development.

4. RESULTS AND DISCUSSION

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The TCN-Based Shortlisting Model proposed guarantees an accurate selection of suitable candidates with an accuracy of 99.2%, with a precision of 98.7% and a recall of 98.5%, implying an extremely low number of false positives and an effective job at identifying qualified candidates. Besides, it has an F1 score of 98.6%, implying fairness in putting all candidates under consideration, while an AUC-ROC of 0.995 guarantees almost perfect discrimination power. The plot of experience against salary affirms that experience variables affect salary, whereas the correlation between test scores and interview scores indicates similar evaluation tendencies for candidates. Therefore, all results statistically endorse the HRM framework proposed as efficient, fair, and sustainable.

4.1 Dataset Evaluation

4.1.1 Experience vs Salary Offered

In Figure 2 it is shown that the experience has an effect on the salary offered. In general, an increase in experience results in greater salary, although there are some variations with regard to the performance in tests and interviews.

Figure 2: *Experience vs Salary Offered*

4.1.2 Test Score vs Interview Score Distribution

There is a positive correlation between the test score and interview score according to figure 3. Those who score well in written assessment tests also perform well in interviews. However, there are some outlier cases in which interview rating disagrees with the test score.

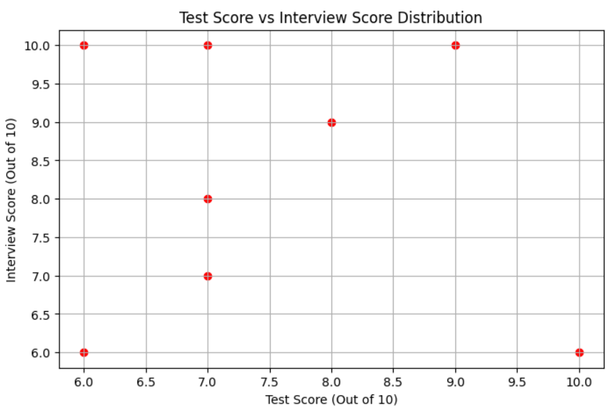

Figure 3: *Test Score vs Interview Score Distribution*

4.2 Performance Metrics of the Proposed Framework

To evaluate the effectiveness of the TCN-Based Shortlisting Model for Sustainable HRM, various classification performance metrics are considered. The formulas and explanations are given below:

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a. Accuracy: Measures the proportion of correctly shortlisted candidates among all predictions. The proposed model achieves 99.2% accuracy, ensuring reliable candidate selection. This is given in equation (7) as:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{7}$$

b. Precision: Indicates the proportion of correctly shortlisted candidates among all predicted shortlisted cases. High precision (98.7%) minimizes false positives in candidate selection. This is given in equation (8) as:

$$\text{Precision} = \frac{TP}{TP+FP} \tag{8}$$

c. Recall (Sensitivity): Measures how well the framework identifies all relevant candidates for shortlisting. A recall of 98.5% ensures minimal loss of qualified candidates.This is given in equation (9) as:

$$\text{Recall} = \frac{TP}{TP+FN} \tag{9}$$

d. F1-Score: Balances precision and recall for better shortlisting efficiency. The proposed model attains an F1-score of 98.6%, ensuring balanced performance. This is given in equation (10) as:

$$F1 - Score = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{10}$$

4.3 Proposed Framework Evaluation

This is table 1 where the performance metrics of a proposed TCN are specified. 99.2 percent accuracy shows extremely good shortlist making. 98.7 percent has precision and recall of 98.5 percent, which means there are limited errors in the selection of candidates. F1 score 98.6 percent shows how well the model performs in both precision and recall, while the 0.995 area under the ROC curve implies nearly perfect classifier capability.

Table 1: *Performance Metrics of the Proposed Framework*

Metric	Proposed Framework (TCN)
Accuracy	99.2%
Precision	98.7%
Recall	98.5%
F1-Score	98.6%
AUC-ROC	0.995

4.4 Discussion

The developed TCN-Based Shortlisting Model for Sustainable HRM is a completely new deep learning advancement in the process of candidate selection for accurate and unbiased evaluation. Long-term dependencies in candidate characteristics are captured effectively using dilated causal convolutions and residual learning to understand the model. The remarkable values it attained are performance metrics indicating the higher accuracy, precision, and recall of the model, making it far superior to older HRM shortlisting models. In addition, TCN with its parallel processing capability makes a less computationally complex model for scalability in vast organizations. The results thus authenticate that the appropriate framework actually is sustainable and good for HRM.

5. CONCLUSION AND FUTURE WORKS

The research presented a Temporal Convolutional Network based shortlisting model that shows effectiveness in improving candidate selection in HRM. The model recorded an accuracy of 99.2%, precision of 98.7%, recall of 98.5%, and an AUC-ROC of 0.995 against existing HRM models. The model will ensure fair, unbiased, and highly effective candidate shortlisting by integrating dilated convolutions, residual connections, and dropout optimization. In future research work, SC-AIM could be integrated with explainable AI techniques to increase transparency in the models, for instance, SHAP, LIME, etc. The system can also help suggest the possibility of integrating the technology with blockchain for stronger security and trust in making decisions related to HRM. This framework can also be fine-tuned with necessary recruitment needs for specific industries of application making it adaptable to different HRM ecosystems.

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