# AI-Driven Labor Market Forecasting: Predicting Sectoral Shifts And Demand For Future Skills

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Recent advances in artificial intelligence (AI) and deep learning (DL) have significantly improved the ability to analyze and forecast economic and labor market trends. However, accurately predicting sector-specific employment remains challenging due to nonlinear relationships among macroeconomic variables and long-term temporal dependencies that traditional econometric and recurrent models often fail to capture. To address these limitations, this study proposes a multivariate deep learning approach based on the Patch Time Series Transformer (PatchTST) architecture. The model is designed to forecast labor market dynamics, identify sectoral employment trends, and analyze evolving patterns of future skill demand. The proposed framework utilizes structured data from the International Labour Organization Statistics (ILOSTAT), incorporating key indicators such as employment, unemployment, inflation, and productivity. Data preprocessing techniques, including missing value imputation, temporal alignment, outlier treatment, and z-score normalization, are applied to ensure data quality and consistency. The time series data are further transformed into modelcompatible inputs using sliding-window sequences and patch-based segmentation, enabling efficient learning within the Transformer architecture. PatchTST leverages multi-head selfattention mechanisms to capture complex temporal patterns and inter-sectoral relationships, allowing for accurate multi-horizon forecasting. Experimental results demonstrate strong predictive performance, with a Mean Absolute Error (MAE) of 0.0103 , Root Mean Squared Error (RMSE) of 0.0161 , Mean Squared Error (MSE) of 0.0003 , and an $R^2$ value of 0.9906 , indicating a close fit between predicted and actual values. Overall, the findings suggest that the proposed model provides a robust, scalable, and data-driven solution for workforce planning and future skill demand analysis.

**Keywords:** AI, Labor market forecasting; Sectoral employment forecasting; Future skill demand; DL forecasting; Multivariate time series prediction.

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## 1. Introduction

Computational social science and AI improve nonlinear labor-market forecasting beyond conventional volatility and shock prediction models, Orozco-Castañeda et al. [1]. AI, ANN, ensemble learning, and RF models improve labor-market forecasting accuracy using heterogeneous workforce datasets Liu et al. [2]. Over the past four decades, labor-market forecasting has shifted from traditional econometric models toward ML and DL approaches capable of modeling nonlinear multivariate relationships. Rapid digitalization and automation have increased the need for accurate sectoral employment and skill-demand forecasting Webb et al. [3]. Simsek et al. [4], Rožman et al. [5], and Sancar and Cavus [6] demonstrated that DL models such as LSTM effectively capture complex temporal labor-market dependencies. Caetano et al. [7] showed Transformers with contextual indicators improved multivariate forecasting and uncertainty estimation. Su et al. [8] found Transformer variants captured long-range temporal dependencies, enhancing forecasting accuracy. The proposed PatchTST framework forecasts sectoral employment shifts and emerging skill-demand patterns using ILOSTAT data.

The principal contributions of the proposed work are the following:

- Develop an AI-based multivariate framework for sectoral labor and skill-demand forecasting using ILOSTAT data.
- Apply preprocessing and sliding-window sequence generation for robust multivariate prediction.
- Use PatchTST to capture nonlinear temporal and intersectoral labor dependencies.
- Evaluate forecasting performance using MAE, RMSE, MAPE, and $R^2$ under rolling-origin validation.

The rest of this paper will be arranged in the following way. Section 1 analyzes similar literature on AI-based forecasting and prediction of the labor market. Section 2 details the proposed methodology and Section 3 describes the findings, experimental design, and comparative discussion. Section 4 sums up the research findings and research directions.

Ergunova et al. [9] highlighted structural employment shifts, while AI forecasting supports workforce planning and skill prediction. Nonlinear macroeconomic interactions such as inflation fluctuations, productivity variation, and unemployment shifts influence sector-specific employment patterns differently across agriculture, industry, and service sectors. These interconnected economic behaviors increase forecasting complexity and create dynamic labor market dependencies over time. Therefore, advanced AI-based forecasting models are essential for accurately capturing multivariate labor market transitions and evolving employment structures. For example, declining agricultural employment may increase workforce migration toward industrial and service sectors, while industrial growth can simultaneously create additional service-related job demand. These cross-sectoral interactions generate complex nonlinear employment dependencies that require advanced forecasting models for accurate labor-market prediction.

Existing literature remains descriptive and lacks integrated AI-based forecasting frameworks with empirical labor-market validation Choiri [10] advanced ML forecasting, yet integrated scalable labor-skill prediction remains unresolved. AI, NLP, DL, and LLMs improved forecasting scalability, but integrated labor-skill prediction frameworks remain limited. Demographic changes such as population aging, low fertility, and rural to urban migration have a great impact on the nature of employment in different industries. Demographic factors influence labor availability and increase industrial workforce demand beyond agricultural sectors.

Table 1 presents a comparative summary of existing labor-market forecasting studies based on their methods, datasets, and major limitations. The comparison identifies scalable multivariate forecasting gaps, justifying the proposed PatchTST labor forecasting framework.

## 2. Materials and methods

The framework forecasts sectoral employment dynamics and emerging skill-demand patterns using multivariate ILOSTAT labor-market data. The structured ILOSTAT dataset has limited regional and skill-level granularity, while restricted temporal depth may constrain detailed representation of evolving workforce dynamics. These limitations justify advanced preprocessing and PatchTST-based multivariate labor forecasting. The framework preprocesses multivariate labor indicators for consistent Transformer-based forecasting using sliding-window sequence generation. Interpolation preserved temporal continuity, while normalization, outlier treatment, and sliding-window preprocessing improved numerical stability, convergence consistency, and multivariate labor forecasting robustness against irregular fluctuations.

Outlier treatment reduces abnormal employment fluctuations, improving Transformer stability and multivariate forecasting reliability during shocks. The data has been processed, and then it is inputted to the PatchTST-based forecasting model. Patch embedding and Transformer encoder layers are used to model nonlinear temporal dependencies and inter-sectoral comovements. PatchTST improves scalable multivariate forecasting through attention mechanisms, patch segmentation, robustness, temporal learning, and inter-sectoral dependency modeling. The framework performs robust multi-horizon employment forecasting and skilldemand prediction using rolling-origin validation metrics. Rolling-origin validation improves forecasting reliability by evaluating the model across sequential temporal windows, enabling consistent multi-horizon prediction, temporal generalization, and robustness under changing macroeconomic and labor-market conditions. Fig. 1 shows the workflow of PatchTST-based sectoral forecasting and skill demand prediction.

The framework integrates synchronized multivariate ILOSTAT labor indicators [11] for deep learning-based labor-market forecasting. The workflow integrates prepro-

**Table 1.** Comparative Summary of Existing Labor Market Forecasting Studies

| Ref. | Method / Model | Focus | Limitation |
|---|---|---|---|
| [1] | Econometric Model | Labor forecasting | Weak nonlinear learning |
| [2] | ANN / RF / Ensemble ML | Employment prediction | Limited temporal learning |
| [4] | LSTM Model | Temporal forecasting | Weak long-horizon learning |
| [5] | DL Forecasting | Sectoral employment analysis | No skill-demand integration |
| [6] | LSTM Forecasting | Labor dependency analysis | Limited inter-sectoral modeling |
| [7] | Transformer Model | Time-series forecasting | Limited labor-market application |
| [8] | Transformer Variants | Long-term forecasting | Limited sectoral analysis |
| [11] | ML Forecasting | Workforce prediction | No integrated framework |
| [12] | AI / NLP / LLM Models | Skill-demand forecasting | Limited multivariate forecasting |
| Proposed Work | PatchTST Framework | Sectoral forecasting | Improved multivariate forecasting |

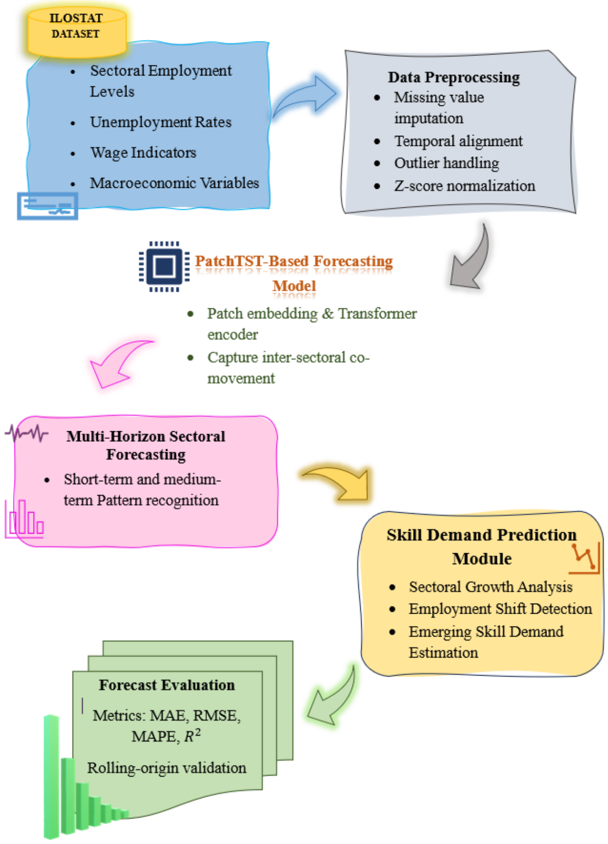


**Fig. 1.** PatchTST-Based Multivariate Framework for Sectoral Employment Forecasting and Skill Demand Prediction Using ILOSTAT Data

cessing, PatchTST encoding, and multi-horizon forecasting with attention-based temporal dependency learning and performance evaluation.

Assume the representation of the ILOSTAT-based international labor dataset as Eq. (1):

$$\mathbf{X} \in \mathbb{R}^{T\times C} \tag{1}$$

Where X: Multivariate ILOSTAT labor time-series matrix, T: Number of time observations, C: Number of labor-market features, $\mathbf{R}^\wedge(\mathbf{T}\times\mathbf{C})$ : Real-valued matrix with time rows and feature columns.

ILOSTAT labor data were preprocessed using interpolation for stable, consistent, transformer-compatible multivariate forecasting performance, as in Eq. (2).

$$\hat{x}_{t,c} = x_{t-1,c} + \frac{x_{t+1,c} - x_{t-1,c}}{2} \tag{2}$$

Where $\hat{x}_{t,c}$ denotes the imputed value of feature $c$ at time $t$, $x_{t-1,c}$ and $x_{t+1,c}$ are the observed values adjacent to one another, $t \in \{1,\ldots,T\}$ and $c \in \{1,\ldots,C\}$ correspond to temporal observations and labor features, respectively.

Temporal synchronization and feature standardization ensured stable optimization and consistent multivariate labor-market forecasting performance as in Eq. (3):

$$\tilde{x}_{t,c} = \frac{x_{t,c} - \mu_c}{\sigma_c} \tag{3}$$

- $\tilde{x}t,c$ is the normalized feature value,
- $x_{t,c}$ is the original labor observation,
- $\mu_c = \frac{1}{T}\sum_{t=1}^{T} x_{t,c}$ represents the mean of feature $c$,
- $\sigma_c = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(x_{t,c}-\mu_c)^2}$ is the standard deviation of feature $c$, is its standard deviation.

Normalization improves numerical stability, while PatchTST captures nonlinear temporal and inter-variable labor-market dependencies. Fig. 2 illustrates the PatchTST Transformer encoder pipeline for forecasting from time series input to prediction output.

Normalized multivariate labor sequences $\mathbf{X}_i \in \mathbb{R}^{L\times C}$, were processed using PatchTST, where L denotes historical length, and C represents forecasting variables. Multi-head self-attention was used to estimate inter-patch dependencies by processing the embedded patch matrix $\mathbf{Z} \in \mathbb{R}^{N\times d}$ as Eq. (4):

$$\text{Attention}(Q,K,V) = \text{softmax}\left(\frac{QK^\top}{\sqrt{d_k}}\right)V \tag{4}$$

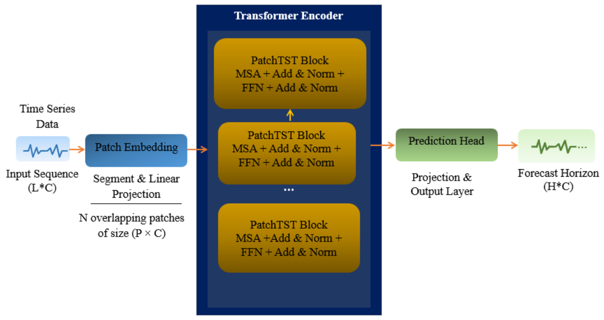


**Fig. 2.** PatchTST-Based Multivariate Transformer Architecture for Sectoral Employment Forecasting

Where $Q = \mathbf{Z}WQ$ (query matrix), $K = ZW_K$ (key matrix), $V = ZWV$ (value matrix), $WQ, WK, WV \in \mathbb{R}^{d\times dk}$ are learnable projection weights, $d_k = d/h$ is the dimension per attention head, $h = 8$ is the number of attention heads.

Attention mechanisms capture inter-sectoral dependencies and macroeconomic co-movements, improving nonlinear multivariate labor-market forecasting through diverse temporal relationship learning. The model is capable of dynamically giving relevance to past labor patches in predicting future employment prospects within the sector by using this mechanism The default dropout is applied with the rate of 0.2 in order to decrease overfitting.

The encoder stack consisted of:

The framework uses four $L_e = 4$ Transformer encoder layers, embedding dimension d = 128, eight attention heads, Number of attention heads $h = 8$, and patch length P = 16.

The framework balances computational efficiency, long-term dependency learning, and stable multi-horizon forecasting across 100 training epochs. Sliding-window analysis preserves sequential temporal context through overlapping historical sequences, improving temporal representation learning and modeling of evolving multivariate employment patterns across long forecasting horizons.

Dropout ($\delta = 0.2$), early stopping, and Algorithm 1 improved PatchTST generalization and training stability.

"'latex "'

## 3. Result and discussion

PatchTST uses ILOSTAT data and rolling-origin validation for reliable multivariate labormarket forecasting performance. System Configuration and Software Environment for Model Implementation and Evaluation include an Intel(R) Core (TM) i9-14900K processor, 32 GB RAM, Windows 11 Home, Python 3.10.19, PyTorch 2.2.2+cpu, NumPy 1.24.3, Pandas 2.3.3, Matplotlib 3.10.8, and Scikit-Learn

**Algorithm 1.** PatchTST-Based Sectoral Employment Forecasting

**Require:** Normalized multivariate time-series $\mathbf{X} \in \mathbb{R}^{L\times C}$
**Ensure:** Multi-horizon forecast $\hat{\mathbf{Y}} \in \mathbb{R}^{H\times C}$

Partition $\mathbf{X}$ into overlapping patches of length $P$ with stride $S$
Form the patch sequence $\mathbf{p}_1, \mathbf{p}_2, \dots, \mathbf{p}_N$, where $\mathbf{p}_j \in \mathbb{R}^{P\times C}$
**for** each patch $\mathbf{p}_j$ **do**
    Flatten and project: $\mathbf{z}_j = \mathbf{W}_e \operatorname{vec}(\mathbf{p}_j) + \mathbf{b}_e$
Construct the embedded sequence $\mathbf{Z} = [\mathbf{z}_1, \mathbf{z}_2, \dots, \mathbf{z}_N]$
**for** each Transformer encoder layer **do**
    Apply Multi-Head Self-Attention:

$$\text{Attention}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{softmax}\left(\frac{\mathbf{Q}\mathbf{K}^{\mathrm{T}}}{\sqrt{d_k}}\right)\mathbf{V}$$

    Apply Feed-Forward Network:

$$\text{FFN}(\mathbf{x}) = \max\left(0, \mathbf{x}\mathbf{W}_1 + \mathbf{b}_1\right)\mathbf{W}_2 + \mathbf{b}_2$$

Apply a linear projection to the final representations
Generate the multi-horizon forecast $\hat{\mathbf{Y}}$

1.3.0.

Table 2 presents PatchTST hyperparameters for efficient multivariate labor-market forecasting, scalability, and generalization performance.

This subsection evaluates PatchTST forecasting performance using complementary regressionbased error metrics. Eq. (5) was used to compute MAE:

$$\text{MAE} = \frac{1}{HC}\sum_{h=1}^{H}\sum_{c=1}^{C}\left|y_{h,c} - \hat{y}_{h,c}\right| \tag{5}$$

where $yh, c$ is the observed labor value and $\hat{y}h, c$ is the prediction. RMSE was defined as Eq. (6):

$$\text{RMSE} = \sqrt{\frac{1}{HC}\sum_{h=1}^{H}\sum_{c=1}^{C}(yh, c - \hat{y}h, c)^2} \tag{6}$$

Mean Absolute Percentage Error (MAPE) was computed as Eq. (7):

$$\text{MAPE} = \frac{100}{HC}\sum_{h=1}^{H}\sum_{c=1}^{C}\left|\frac{y_{h,c} - \hat{y}h_{h,c}}{yh, c}\right| \tag{7}$$

The coefficient of determination $R^2$ was defined as Eq. (8):

$$R^2 = 1 - \frac{\sum(y - \hat{y})^2}{\sum(y - \bar{y})^2} \tag{8}$$

**Table 2.** Hyperparameter Settings of the Proposed PatchTST Forecasting Model

| Model Component | Hyperparameter Group | Values Used | Description |
|---|---|---|---|
| PatchTST Model | Input Configuration | Input sequence length = 48 | Defines the number of past time steps used for learning temporal dependencies |
| PatchTST Model | Forecasting Setup | Horizon = 4 (short-term), 12 (medium-term) | Enables multi-horizon prediction of employment dynamics |
| PatchTST Model | Data Preprocessing | Z-score normalization | Standardizes features for stable training and faster convergence |
| PatchTST Model | Patch Configuration | Patch length = 16, stride = 8 | Segments the time series into overlapping patches for efficient long-term representation |
| PatchTST Model | Embedding Layer | $d_{\text{model}} = 128$ | Transforms input patches into a high-dimensional feature space |
| PatchTST Model | Transformer Encoder | Encoder layers = 3, attention heads = 8 | Captures temporal dependencies and inter-feature relationships using self-attention |
| PatchTST Model | Feed-Forward Network | Dimension = 256, activation = GELU | Enhances nonlinear feature transformation and model expressiveness |
| PatchTST Model | Regularization | Dropout = 0.2 | Prevents overfitting and improves generalization |

Mean observed labor values, residual variance, and total variance support rolling-origin validation for stable PatchTST generalization and dependency learning.

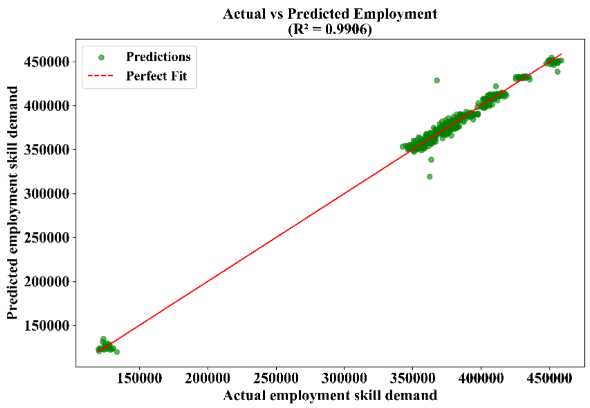


**Fig. 3.** Actual vs Predicted Sectoral Employment Using PatchTST Model

Fig. 3 shows strong agreement between actual and predicted employment values, with $R^2 = 0.9906$ indicating accurate learning of temporal and inter-sectoral dependencies for reliable multi-horizon labor-market forecasting.

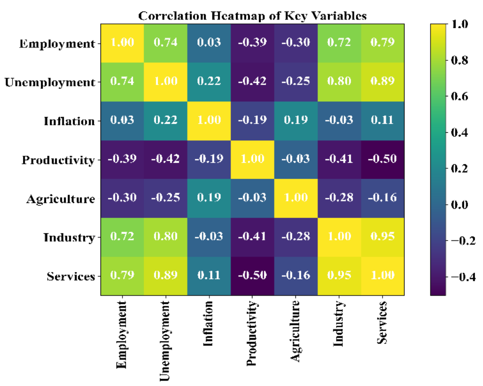


**Fig. 4.** Training and Validation Loss Convergence of the PatchTST Model

Fig. 4 demonstrates stable PatchTST convergence, minimal overfitting, and reliable multihorizon labor-market forecasting performance.

Fig. 5 highlights sectoral employment transitions and intersectoral labor dependencies within the PatchTST forecasting framework.

Fig. 6 shows sectoral skill-demand trends, supporting workforce planning and long-term labor-market decision analysis.

Table 3 presents sector-wise skill-demand projections, highlighting industrial growth, service stability, agricul-

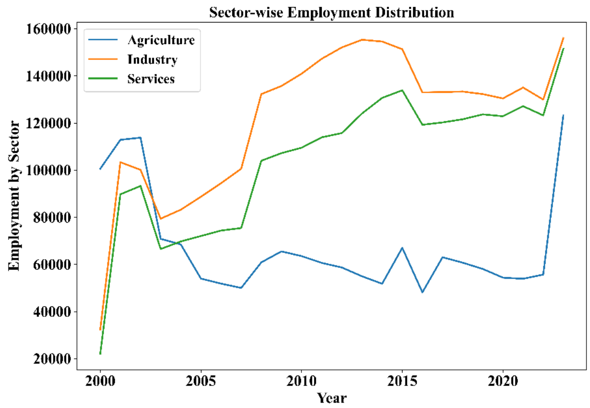


**Fig. 5.** Sector-wise Employment Trends Across Agriculture, Industry, and Services

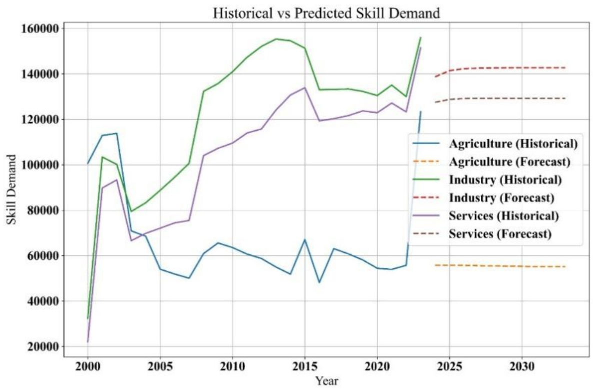


**Fig. 6.** Historical vs Predicted Skill Demand Across Sectors

tural decline, and workforce planning insights. Agricultural employment fluctuations may be influenced by technological transformation and automation, leading to workforce redistribution toward industrial and service sectors. These transitions reflect longterm structural economic modernization.

Fig. 7 shows low prediction bias, strong generalization, and reliable PatchTST forecasting across labor-market sequences. PatchTST captures nonlinear employment behavior while maintaining stable, robust forecasting across varying temporal labor-market conditions.

Fig. 8 demonstrates high forecasting accuracy, low prediction variance, and reliable multihorizon PatchTST forecasting performance.

The ablation study evaluates PatchTST components affecting forecasting accuracy, robustness, and multivariate labor-market prediction performance.

Table 4 shows that PatchTST achieves the lowest errors ( $\mathrm{MSE} = 0.0003$, $\mathrm{MAE} = 0.0103$, $\mathrm{RMSE} = 0.0161$) and

**Table 3.** Sector-wise Skill Demand Growth Analysis Based on Predicted Trends

| Skill Sector | Start Value | End Value | Growth | Growth (%) | Trend |
|---|---|---|---|---|---|
| Industry | 1,38,078 | 1,41,361 | 3,283 | 2.38% | Increasing |
| Services | 1,24,877 | 1,25,155 | 279 | 0.22% | Stable |
| Agriculture | 55,374 | 54,765 | -609 | -1.10% | Decreasing |

**Table 4.** Ablation Analysis of PatchTST Components on Forecasting Performance

| Model Variant | MSE | MAE | RMSE | MAPE | $R^2$ |
|---|---|---|---|---|---|
| Without Patch Embedding | 0.0006 | 0.0189 | 0.0247 | 0.0178 | 0.9712 |
| Without Attention | 0.0007 | 0.0205 | 0.0263 | 0.0191 | 0.9658 |
| Without Normalization | 0.0005 | 0.0158 | 0.0219 | 0.0135 | 0.9826 |
| Without Sliding Window | 0.0006 | 0.0172 | 0.0238 | 0.0152 | 0.9784 |
| Full Model (Proposed PatchTST) | 0.0003 | 0.0103 | 0.0161 | 0.01 | 0.9906 |

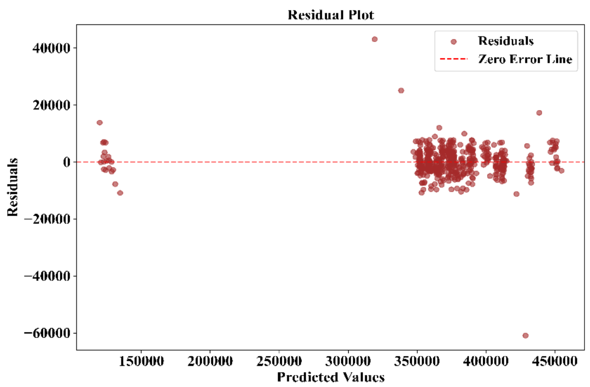


**Fig. 7.** Residual Analysis of PatchTST Model Predictions

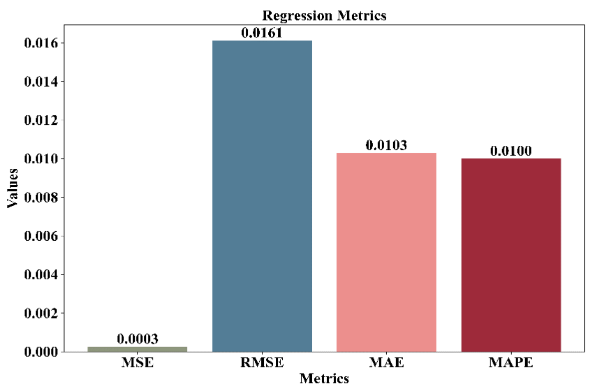


**Fig. 8.** Quantitative Evaluation of Forecasting Performance Metrics

highest accuracy $(R^2 = 0.9906)$. Socioeconomic variables, normalization, and sliding-window techniques improve temporal learning and multivariate labor-market forecasting accuracy.

Table 5 shows that PatchTST achieves low errors (MAE = 0.0103, RMSE = 0.0161) and high accuracy $(R^2 = 0.9906)$. Sectoral employment variations support workforce planning, policy analysis, skill development, and long-term labor-market transformation understanding.

## 4. Conclusion

This paper has introduced a multivariate DL forecasting model of sector-specific labor dynamics using structured ILOSTAT macro-labor data on the PatchTST architecture. The technique theorized combines the major labor indicators, such as employment, unemployment, and macroeconomic variables, in a pipeline of transformers in order to grasp long-term temporal dynamics, as well as nonlinear inter-sector relations. The outcome of the experiments shows a high predictive accuracy with MAE = 0.0103, RMSE = 0.0161, MSE = 0.0003, and $R^2 = 0.9906$, which means that there is an almost perfect correlation between the predicted and actual employment values. The framework has superior forecasting accuracy and better time representation as compared to traditional models and is highly generalized. It is a powerful multi-horizon employment forecasting and data-driven policy analysis tool in a dynamic economic environment due to its capability of effectively handling multivariate time-series data and model complex interactions between labor and other factors. AI-driven labor analytics can support governmental workforce planning and employment policy development through accurate sectoral forecasting. The framework assists in identifying workforce redistribution trends, emerging skill demands, and sector-specific labor changes.

To enhance the model, adding additional macroeconomic variables and variables in the labor market can be incorporated in the model to further foster the degree of accuracy in prediction in the future. Hybrid DL models and transfer learning techniques can also be carried on in the future to get cross-country dynamics of labor. Addition-

**Table 5.** Performance Comparison with Existing Forecasting Models

| Paper | Model | MAE | RMSE | MSE | $R^2$ |
|---|---|---|---|---|---|
| [12] | Regression-Based Forecasting | 0.412 | 0.987 | 0.974 | 0.81 |
| [13] | ANN Forecasting Model | 0.276 | 0.745 | 0.555 | 0.89 |
| [4] | LSTM Deep Learning Model | 0.192 | 0.516 | 0.266 | 0.94 |
| [14] | Informer | 0.0452 | 0.0678 | 0.0046 | 0.9412 |
| [15] | iTransformer | 0.0218 | 0.0352 | 0.0012 | 0.9845 |
| Proposed Work | PatchTST Model | 0.0103 | 0.0161 | 0.0003 | 0.9906 |

ally, explainable AI techniques could help to increase the explainability of the models and enable the policy-oriented study of the labor market.

## 5. Acknowledgement

## 6. Declarations

Data Availability: https://ilostat.ilo.org/data/?cat_mode=subject

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