Development of an Automated Search System for Technology Transfer

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Abstract: Continuous modernization of an enterprise is based on a constant search for "bottlenecks" in production and technologies that could expand them. This approach ensures a sustainable upward trend in production development in the context of constant competition. This article considers the issue of automating this routine task.

1 INTRODUCTION

The relevance of the task of continuous search for technologies for transfer at enterprises is due to several factors related to changes in business conditions, globalization, scientific discoveries and progress (M. Kans, 2024, M. L. Chaves Franz, B. Ostadi, 2024). The importance of this task is due to the following circumstances:

1. Rapid development of technologies

Modern technologies are developing at a tremendous speed. New solutions and innovations appear daily, which requires enterprises to constantly monitor and adapt new technologies to maintain competitiveness.

2. Competitiveness and innovations

In order to stay afloat in a highly competitive environment, enterprises must actively implement innovations. Continuous technology research helps identify unique techniques and processes that can increase productivity or reduce costs.

3. Globalization

With increasing globalization, companies are faced with the need to adapt technologies that have been proven and implemented in different countries and markets. This requires a systematic approach to technology transfer to ensure their successful integration into new conditions.

4. Adaptation to market changes

The market is constantly changing, including in response to changes in consumer preferences, legislative initiatives and economic conditions. Carrying out continuous technology research allows companies to quickly adapt to these changes and remain relevant.

5. Environmental and social requirements

With sustainability and environmental regulations in mind, companies need to find and implement technologies that help reduce negative impacts on the environment. This may include the use of clean technologies, efficient resource management and carbon neutral solutions.

6. Cost reduction and increased efficiency

Finding and implementing new technologies can lead to significant cost reductions and increased overall efficiency. Effective solutions can optimize processes, improve product quality, and reduce costs.

7. Innovation Culture

Creating a culture that encourages innovation and experimentation can be a key competitive advantage for businesses. Continuous technology discovery supports this culture by encouraging employees to be creative and adaptive.

8. Integration and Partnership

Continuous technology discovery also includes the ability to collaborate with academic institutions,

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startups, and other businesses. This provides an opportunity to leverage external knowledge and resources, which can also contribute to successful technology transfer (J. M. Kim 2024, L. Janecki, 2024).

Thus, continuous technology discovery is an important task for modern businesses that want to remain competitive and adapt to change. It allows not only to introduce innovations, but also to optimize processes, reduce costs, and ensure sustainable growth in an ever-changing market (X. Yang, 2023, V. M. Tabim, 2024).

2 METODOLOGY

Automated technology discovery is the process of using modern information and analytical systems to identify, analyze, and evaluate technologies that can be adapted, licensed, or implemented in other industries or businesses. The key aspects of automating this process are:

1. Defining goals and requirements:

• Defining the scope: it is necessary to determine which industries or processes require modern technologies.

• Formulating criteria: it is necessary to decide which characteristics of technologies are most important (cost, efficiency, innovativeness, etc.).

2. Data management systems:

- Database creation: preparation of a structured database including information on existing technologies, patents, scientific publications and startups.

- Using APIs: integration with various external databases and scientific repositories via API allows automating the collection of information.

3. Search technologies and algorithms:

- Machine learning and AI: Use machine learning algorithms to analyze and search for relevant patents, publications and innovations based on specified criteria.

- Neuro-linguistic models (NLP): Algorithms for processing verbal information can help in analyzing the texts of scientific publications and patents to identify hidden patterns and technologies.

4. Technology assessment and analysis:

- Assessment criteria: it is necessary to develop a system of assessment methods that will allow to compare different technologies by important parameters.

- Modelling and simulation: implementation of models for predicting the effectiveness of technologies in new conditions.

5. Visualization and reporting:

- Interactive panels: dashboards for visualization and analysis of data on current technologies and trends.

- Automatic report generation: a system for generating regular reports based on the results of search and analysis.

6. Networking:

- Knowledge sharing platforms: use of specialized platforms for communicating with experts and exchanging experience in technology transfer.

- Participation in events: automation of the processes of searching and keeping records of events aimed at technology transfer.

7. Legal aspects:

- Patent monitoring: Automate the process of tracking new patents and licenses in areas of interest.

- Legal Compliance: Ensure that all search results comply with legal regulations and standards.

Automated search for technologies for transfer is a multi-stage process, which includes the use of various technologies and approaches. Implementation of AI-based systems, big data analysis and the use of modern platforms for knowledge sharing will help to significantly simplify and speed up this process (S. K. G. Saroar, 2024).

In this regard, it is proposed to develop an automated system for searching technologies for transfer for enterprises.

3 RESULTS

The architecture of a system for continuous search for technologies for transfer in enterprises can be multi-layered and include various components that work together to automate the process of searching, analyzing and implementing technologies. Such an architecture might look like this (Fig. 1):

1. Data Collection Layer

- Data Sources: A variety of data sources, such as:

- Scientific publications and articles

- Patent databases

- Databases of startups and innovative companies

- Industry reports and analytics

- Social networks and professional platforms (e.g. LinkedIn)

- Websites and blogs related to technology news

- Data Collection Tools: Using web scrapers, APIs for integrating with external sources, and systems for parsing open data.

2. Data Storage Layer

- Database: Storing the collected data in a relational (e.g. PostgreSQL) or NoSQL (e.g. MongoDB) database.

- Big Data Storage: Using Hadoop or Apache Spark to process and analyze large amounts of data.

3. Data processing and analysis layer

- Analytics models: Machine learning and natural language processing (NLP) algorithms for:

- Classification and categorization of technologies

- Identification of hidden patterns and trends

- Analysis of sentiment and descriptions in texts

- Visualization systems: Dashboards and visual tools (e.g. Tableau, Grafana) for presentation of key indicators and analysis results.

4. Technology Assessment Layer

- Assessment Methodologies: Develop KPIs and criteria for evaluating technologies (e.g. ROI, degree of innovation, compliance).

- Modelling and Simulations: Tools for assessing the impact and effectiveness of new technologies in the context of the enterprise.

5. User Interaction Layer

- User Interface: Web interface or mobile application for accessing the system, interacting with and interacting with data.

- Dashboards: Interactive dashboards for downloading reports, receiving notifications about new technologies and monitoring the status of implementation.

6. Integration Layer

- API: Interfaces for integration with other internal enterprise systems (e.g. ERP, CRM) for data exchange and process automation.

- Integration with external platforms: Interaction with research institutes, startups and other organisations that can offer their technologies for transfer.

7. Monitoring and Feedback Layer

- Monitoring Systems: Tools for tracking key system performance indicators, such as the number of technologies found, the success of implementation, and user satisfaction.

- User Feedback: Collecting and analyzing user feedback to improve the system and adapt its functionality.

It should be noted that such an architecture can be adapted depending on the specific needs of the enterprise, available resources and technological capabilities. It is also important to consider data security and compliance with legal regulatory standards when developing and implementing such a system.

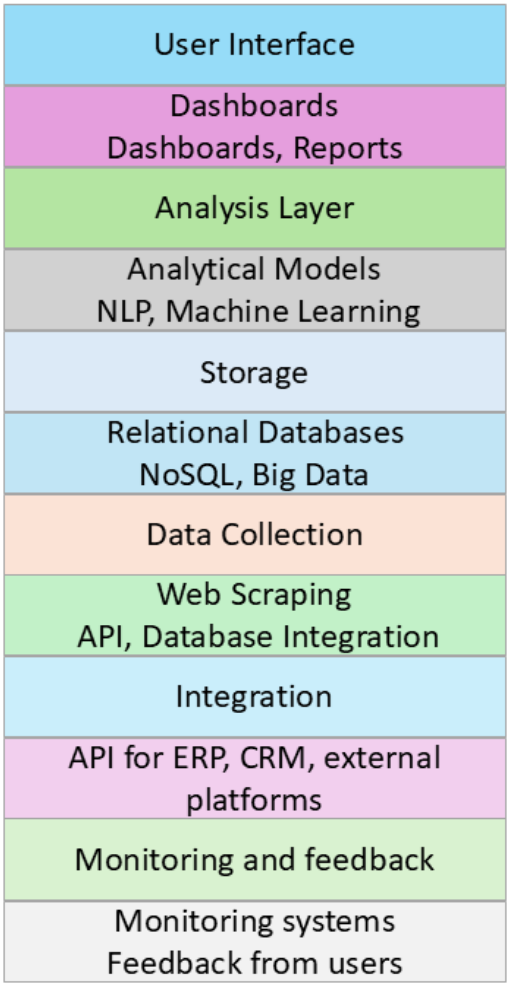

Figure 1: System architecture.

3.1 Module Development

1. Data analysis layer.

The data analysis layer in the continuous discovery technology system is responsible for processing, analyzing, and interpreting the collected information. The main tasks of this layer may include data processing, knowledge extraction, modelling, and visualization of results. The software implementation of the data analysis layer includes the use of libraries for statistics, machine learning, and data visualization.

The main components of the data analysis layer:

1. Data preparation:

- Data cleaning and preprocessing (e.g., removing gaps, normalizing).

- Data filtering and aggregation.

2. Analysis and modelling:

- Applying statistical methods and machine learning algorithms.

- Building models for prediction and classification.

3. Visualization:

- Presenting the analysis results using graphs and charts.

Possible extensions:

- Adding other machine learning algorithms: More complex models or ensemble methods can be used to improve accuracy.

- Time series analysis: If the data contains timestamps, time trend analysis can be added.

- Studying correlations: It is possible to identify how different factors influence technologies or their success.

- Interactive visualization: Using libraries such as `Plotly` or `Bokeh` to create more interactive graphs.

2. AI Models

The Analytics Models module, which includes Natural Language Processing (NLP) and Machine Learning, is a key part of the data analytics system. This module is responsible for applying various algorithms to extract, process and analyze knowledge from text data, as well as to perform predictions and classifications.

The Figure 1 shows the structure of this module.

The main components of the Analytics Models are:

1. Text Processing (NLP):

- Tokenization

- Stop word removal

- Lemmatization and stemming

- Text to vector representation (e.g. TF-IDF or Word

Embeddings)

2. Machine learning models:

- Classification (e.g. Naive Bayes, SVM, or decision trees)

- Clustering (e.g. K-Means)

- Regression (e.g. linear regression for prediction)

- Building and training models on prepared data

3. Model evaluation:

- Evaluation metrics (precision, recall, F1-score for classification)

- Cross-validation

4. Model application:

- Make predictions on new data

- Interpretation of results (e.g. feature importance)

This analytical module provides powerful tools for natural language processing and applying machine learning to textual data. This code can be adapted to work with different tasks and data and extended with additional models and analysis functions.

3. The data collection layer of a continuous technology discovery system may include several software components and tools that interact to efficiently extract information from various sources. The main elements are presented below, along with sample code to illustrate how the parts of this layer work.

The main components of the data collection layer are:

1. Data access modules:

- Web scrapers: Automated scripts for obtaining information from websites.

- API clients: Libraries for working with third-party APIs (e.g., patent databases, scientific publications).

- Document parsing systems: For working with PDF, DOCX, and other documents.

2. Task schedulers:

- Used to periodically execute data collection scripts (e.g., `cron` on Linux or `Task Scheduler` on Windows).

3. Message queues:

- Systems such as RabbitMQ or Apache Kafka can be used to process data in real time.

4. Data warehouse:

- Temporary storage for saved data before further processing (e.g. JSON files).

This approach to developing the data collection layer allows for automatic extraction of technology information from various sources and integration into the system. The functionality can be further adapted and expanded for specific enterprise needs.

4. The monitoring and feedback module in the analytics system is an important part that allows you to track model performance, receive feedback from users, and make adjustments to improve the system. This module can include functions for monitoring model performance indicators, collecting user feedback, and advanced reporting.

The main components of the monitoring and feedback module are:

1. Performance monitoring:

- Track model metrics (e.g. accuracy, recall, F1-score).

- Regularly test on new data to assess model stability.

2. Feedback collection:

- Collect feedback from end users on model predictions.

- Store and analyse feedback to adjust the model.

3. Reporting and visualization:

- Generate reports on model performance.

- Visualize metrics and feedback using graphs and dashboards.

4. Model update:

- Automated or manual retraining of the model based on collected data and feedback.

The monitoring and feedback module provides critical functionality to assess the performance of analytical models and makes necessary adjustments based on user feedback. Using the Python programming language and the Flask framework, it is easy to create a web service that collects and processes important data to improve the system. This module can be further extended to integrate with alert systems, automate the retraining process, and build more complex dashboards.

5. The interface options of the system itself are shown in Fig. 2.

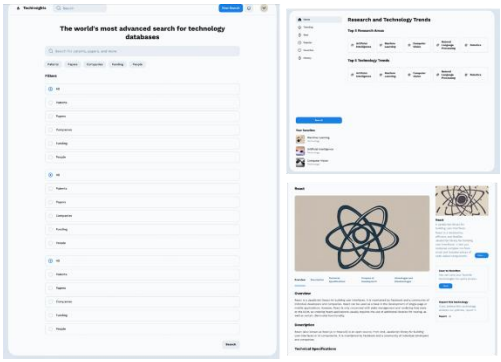

Figure 2: Interface variations.

4 DISCUSSIONS

For today system is on development. We can evaluate it as TRL 3 to TRL 4. Now modules development is on the process. Different approaches and designs are tested. After that approbation on the real production is expected.

We also suggest that this system can be useful not only for production but also for medical organizations where technology transfer is also a very current issue.

5 CONCLUSIONS

The task of finding and optimizing the selection of technologies for subsequent transfer is currently relevant for various industries. Effective organization of work in this area is the key to competitive modern production.

In this ыегвн, the topical issue of automating the search for optimal technologies for transfer was raised. This issue is key to ensuring the competitiveness of a modern enterprise. At present, this area is under-researched - there are not enough systems to solve the abovementioned issue. In this regard, the article proposed the architecture of such a system. Options for developing system modules and its proposed interface are proposed. In the future, it is planned to implement the proposed system at a real enterprise.

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