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APPLICATION OF LSTM NEURAL NETWORK FOR RISK MANAGEMENT IN FINANCIAL TRANSACTIONS TO REDUCE THE SHADOW ECONOMY

The financial sector faces various risks, with fraud in transactions being particularly significant. As electronic payments and online transactions grow, fraud schemes are becoming more sophisticated, posing challenges for financial institutions. Therefore, risk management is crucial for maintaining financial stability and protecting client assets. Modern technologies, especially machine learning, provide new opportunities for detecting anomalies and predicting risks. LSTM (Long Short-Term Memory) neural networks are promising because they can process sequential data and identify complex time dependencies. Their ability to store information over time allows LSTM to analyze historical transaction data effectively and detect patterns indicative of fraud. The use of LSTM in financial risk management is important for its capacity to detect complex patterns in large volumes of transaction data, enabling timely responses to fraudulent activities and reducing potential losses [1, p.5].

The novelty lies in integrating LSTM into risk management processes, providing more accurate forecasting and analysis of financial risks compared to traditional approaches. This enhances transaction control and overall financial security. Moreover, LSTM plays a crucial role in reducing the shadow economy, which is linked to high levels of fraud, money laundering, and illegal activities, ultimately threatening economic stability and tax revenues [2, p.3].

LSTM's ability to detect anomalies enables more effective identification of suspicious activities. By processing sequential data, it uncovers behavioral patterns that traditional methods might miss, which is vital in combating unpredictable fraud in the shadow economy. This empowers financial institutions to take timely actions to mitigate fraud risks and strengthen regulatory frameworks for financial oversight. Financial risk management and the shadow economy are closely related, as unregulated transactions pose significant risks to the stability of the economic system [3, p.5]. With tools like transaction analysis and anomaly monitoring, financial institutions can identify suspicious activities related to the shadow economy. Timely detection allows for preventive measures, protecting legitimate businesses from financial losses. So, in financial risk management, LSTM can be used to assess credit risk, manage market risk, and identify anomalies that may indicate potential financial problems. The formula for the new state is:

$$f_t = \sigma\big(W_f \cdot [h_{t-1}, x_t] + b_f\big) \text{ (forget layer)}$$
$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \text{ (input layer)}$$
$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \text{ (new candidate)}$$
$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \text{ (memory refresh)}$$
$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \text{ (output layer)}$$
$$h_t = o_t \cdot \tanh(C_t) \text{ (output)}$$

where f_t, i_t, o_t - respectively, the forget layer, the input layer and the output layer.

C_t - memory at a moment in time *t*.

h_t - the initial state at the moment of time.

LSTM model steps for risk management:

1. Data Collection: Collection of data about financial transactions, including amounts, types, timing and status (fraudulent or not).

2. Data processing: Normalization of numerical values and coding of categorical data. Formulation of the sequence for the analysis of behavior patterns.
3. Data partitioning: Data partitioning into training and test sets.
4. Building an LSTM model: Creating an LSTM architecture with gates to process the input data and form the output.
5. Model training: The model is trained on the training data, adjusting its parameters to improve accuracy.
6. Model evaluation: Checking the accuracy of the model on test data using metrics such as accuracy and F1-measure.
7. Risk detection: The model predicts the probability of fraud for new transactions and flags suspicious ones [4, p. 6].

So, this process allows to effectively identify and manage the risks of fraud in financial transactions. In summary, the application of LSTM in financial area can contribute to improving the transparency of financial transactions, increasing trust in financial institutions and supporting the development of legal business. Therefore, the implementation of the latest technologies, such as LSTM, in risk management is a critical step to reduce the impact of the shadow economy and improve the overall health of the financial system.,

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МОНІТОРИНГ ТА ОЦІНЮВАННЯ СКЛАДОВИХ РЕГУЛЯТОРНОГО ВПЛИВУ ДЕРЖАВИ НА БАНКІВСЬКУ ДІЯЛЬНІСТЬ

Післявоєнне відновлення національної економіки буде здійснюватися шляхом забезпечення фінансової стійкості банківської системи України, структуризація якої повинна базуватися на метрології провідних індикаторів стабільності та економічних нормативах, що регламентуються Національним банком України (НБУ).